Drivers of Growth in the Modern Economy:
R&D, Innovation, ICT and Human Capital

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Contents

Introduction

The importance of R&D and innovation for productivity and long run economic growth is difficult to overstate. The empirically minded economists started to study the activities that cause productivity growth in the mid-1950s (see the first studies by Schultz, 1953, and Griliches, 1957). From the mid-1980s it has been one of the most active topics of research in both macroeconomic, microeconomic, and applied econometric studies. Although an old topic, there is an ongoing discussion about what are the modern drivers of growth. In the modern economy, firms invest in a wide range of intangible assets, including data, software, patents, new organisational processes and firm-specific skills. Together, these non-physical assets make up a firm's *knowledge-based capital*, KBC (see OECD, 2013). A lack of proper control for intangible assets and underinvestment in KBC are seen as one of the main candidates for explaining the poor productivity performance of European countries relative to the USA.[1] The need for Europe to move into the *knowledge-based economy* and to support investment in KBC has been pronounced by Europe 2020 (the EU's recent growth strategy) as a main goal. Furthermore, increasingly available micro (firm-level) data have made it possible to make significant progress in empirical studies of productivity and economic growth by applying advanced econometric methods to better data. These developments have improved our knowledge of factors behind the success of firms and countries and increased our ability to predict the effects of different policies that impact technologically advanced investments (R&D, human capital, intangibles, etc.).

A first unifying feature of the five essays presented in this dissertation is that they all comprise empirical research and use microeconomic models and microeconometric techniques to analyse factors that contribute to improved business performance. How is new technology adapted by the firm and how does it affect the firm's productivity and the skill composition of the labour force? How should we account for improvements in labour quality and does it matter how we measure human capital in a growth accounting context? Do public policies aiming to increase private investments in R&D result in more innovations and higher firm productivity? What are the factors that stimulate innovation and how do these factors interact? All these questions are highly relevant for Norway.

In their Economic Survey for Norway, OECD (2007, chapter 5) highlighted the importance of innovation and discussed challenges for the Norwegian R&D policy. The OECD was puzzled by the low R&D intensity and stated that "Future economic prosperity [of Norway] will also depend on the pace of technology-driven innovation, which at present remains low by cross-country standard indicators." To promote innovation and growth, the Norwegian government uses different programmes supporting R&D activities and adoption of new technologies. Large amounts of resources

[1] See, for instance, van Ark *et al.* (2003), O'Sullivan (2006) and Hall and Mairesse (2009).

are also used in the education sector, which is important for human capital accumulation. The amount of resources spent and the importance of the outcomes provide a strong motivation for understanding the relationship between inputs, outcomes and different policies.

An explicit aim of the present dissertation is to strengthen knowledge relevant for Norwegian public policies. This policy focus is the second unifying aspect of the present dissertation. While the first and second essays are shedding light on one of the most researched policy topics in the labour demand literature, i.e. skilled-biased technological change; the third, fourth and fifth essays focus on questions that are highly relevant from the R&D and ICT (Information and Communication Technology) policies' perspective. More specifically, the first essay investigates the dynamics (among others) of the skill composition of the labour force as a response to investment spikes; the second essay demonstrates (among other results) that the high-tech industries seem to employ and reward workers with especially high skills; the third essay investigates whether SkatteFUNN, a tax-based R&D incentive introduced in Norway in 2002, had positive effect not only on R&D spending, but also on innovation and patenting; the fourth essay addresses the question of whether the returns to R&D differ between R&D projects funded by public grants given by the Research Council of Norway as opposed to privately funded R&D; while the last essay assesses the importance of R&D and ICT investment for firm innovation and productivity.

Both economic theory and empirical evidence suggest that there is a key link between the skill level of the workforce and economic performance, both at the firm and the economy wide level. This idea was first formalised by Nelson and Phelps (1966). In their model, educated workers have a comparative advantage in innovation, imitation and implementation of new technologies. Thus the effect of increased skills should occupy a key role in explaining both economic growth and the change in the wage distribution observed in many countries. Until fairly recently, however, empirical analyses of firms' productivity and success have concentrated on firm characteristics, and less on the characteristics of the workforce, mainly because of data limitations. Availability of longitudinal matched employer–employee data for Norway has made it possible to incorporate labour heterogeneity into all five studies presented in this dissertation both when analysing firm performance and economic growth. This is a third unifying aspect of the dissertation. With respect to this topic, the first essay investigates whether new capital affects among other factors the skill composition of the labour force; the second one focuses on the criteria for classification of workers as high-skilled or low-skilled; and the third, fourth and fifth essays use skill composition of the labour force as one of the control variables.

In addition to controlling for labour heterogeneity, controlling for industry heterogeneity is also an important aspect of my research. For instance, the first essay compares the results for two manufacturing industries with one service industry; the second essay provides separate results for each of the eleven manufacturing industries; and the fifth essay compares manufacturing firms versus firms in services.

Finally, all the essays are empirical, use related econometric methods and there are to a large part data-driven. They utilise different (mostly administrative) data sources maintained by Statistics Norway both at the firm and the individual level. The firm-level data sets include investment statistics, accounts statistics, the Community Innovation Survey and the R&D Survey; while the individual-level data sets include the Register of Employers and Employees, the Pay Statements Register and the Norwegian Educational Database. Availability of consistent systems of identifiers has made it possible to combine these data sets into longitudinal matched employer-employee data, and hence control not only for different firm characteristics, but also for characteristics of the workforce when analysing firm performance. The second essay differs somewhat from the others, in that the observational unit is an individual and not a firm as in the other essays.

The estimation methods and econometric models employed in the dissertation are commonly used in the applied econometric literature: The first essay employs maximum likelihood method for estimation of a Seemingly Unrelated Regression Equations (SURE) system, the second essay employs GLS to estimate wage equations, the third essay employs pseudo maximum likelihood method for estimation of a conditional logit model with selection correction, the fourth essay employs GMM and the fifth essay employs (pseudo) maximum likelihood methods for estimation of both sample selection, multivariate probit and count data models. More detailed summaries of the five essays follow below.

Overview of the dissertation

The first essay, *Lumpy investments, factor adjustments and productivity* (written jointly with Øivind A. Nilsen, Arvid Raknerud and Terje Skjerpen, and reprinted from *Oxford Economic Papers*, **61(1)**, 104–127, January 2009), investigates the dynamics of, and interrelationships between, input and output variables in the periods before and after an investment spike at the firm level. Specifically, it investigates how new technology is adapted by the firm and how it affects the firm's productivity (relative to the industry average). Moreover, it investigates whether new capital affects the skill composition of the labour force. With a few exceptions, the literature on the dynamics of different inputs' demand has considered separate adjustment of a single production factor.[2] However, it is clear

[2] For capital adjustment, see, for instance, Cooper and Haltiwanger (2006) and Letterie and Phan (2007); for labour adjustment, see, for instance, Nilsen *et al.* (2007), Varejão and Portugal (2007) and Kramarz and Michaud (2010).

that lumpy adjustment of one input may be due to non-convexities not only in the technology of adjustment of that input, but also in those of other inputs as well. We can also expect severe biases in the estimates when one input demand parameter is estimated separately from those of other inputs.[3]

In the current study, we focus on simultaneous variations in output, capital, materials, man-hours, labour productivity, the skill composition and hourly cost of labour. First, we argue that common definitions of an investment spike, e.g. an investment ratio exceeding 20%, are inappropriate when analysing a sample consisting of both large and small firms. Hence, we propose a modified definition of an investment spike, where the threshold value is higher for small than for large firms (measured by the size of the equipment capital stock). Then, by using a rich employer–employee panel data set for two manufacturing industries and one service industry[4] in 1995–2003 and following Sakellaris (2004) and Letterie *et al.* (2004), we adopt an explorative econometric approach. All variables are treated as being simultaneously determined. Efficient estimators are obtained by using the method of maximum likelihood.

By applying our definition of an investment spike, we obtained a number of important findings. First, spikes account for a large share of aggregate industry investment. Second, investment spikes are accompanied by almost proportional increases in sales, materials and man hours. Third, two or more years after the spike, there is substantial capital deepening, but labour productivity is relatively unaffected. Fourth, the growth patterns of materials and man hours are similar and much smoother than are those for capital. The observed patterns of factor adjustment indicate the presence of non-convexities in capital-adjustment costs.

The changes in labour productivity associated with investment spikes are small. This may be because investment spikes temporarily disrupt production. The small changes in productivity may indicate that general technological upgrading and increased productivity at the industry level are explained by trend factors, rather than by lumpy investment behaviour. We also found that the skill composition is unaffected by investment spikes. This may suggest that productivity improvements only partly are related to instantaneous technological changes through investment spikes. This finding is consistent with results often obtained in related empirical studies.

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[3] For example, Letterie *et al.* (2004) show that the adjustment of one factor input cannot be understood without considering adjustment of the other inputs, especially when the latter are large. Further, Bloom (2009) finds that a model with labour adjustment costs only, as is typical in the dynamic labour demand literature, is problematic in the sense that the estimated parameters are far away from the true ones found in a model that included both investment and labour adjustment costs. See also the discussion in Addison *et al.* (2014) on the necessity of controlling for adjustments in other inputs used in production when studying the dynamics of labour demand.

[4] The two manufacturing industries are Machinery, NACE 29, and Electrical and optical equipment, NACE 30–33; and the single service industry is Retail trade, NACE 52. All industry definitions here and later are based on SN2002 NACE-codes.

We found interesting differences between the two manufacturing industries and the service industry. Capital adjustments are smoother in the service industry than in the two manufacturing industries. This feature suggests that the structure of capital adjustment costs differs between the capital-intensive manufacturing industries and the relatively labour-intensive retail industry. The responses of sales and input factors (other than capital) to lumpy investments indicate that non-convex adjustment costs are less important in retail trade than in manufacturing industries.

As mentioned in Addison *et al.* (2014), full understanding of the dynamics of input demand requires the specification of models that incorporate all inputs used in production while allowing for interactions between them. However, such modelling is data-demanding and requires availability of comprehensive panel data. Our study is still one of the few ones that focus on interrelated factor demand. As Sakellaris (2004) and Letterie *et al.* (2004), we use a non-structural and explorative approach in our study. Recently, Asphjell *et al.* (2014) have developed a structural model of interrelated factor demand subject to nonconvex adjustment costs. Using simulated method of moments they reveal significant cost advantages of simultaneous adjustments of capital and labour versus sequential adjustments.

The second essay, *The importance of skill measurement for growth accounting* (written jointly with Øivind A. Nilsen, Arvid Raknerud and Terje Skjerpen, and reprinted from *Review of Income and Wealth*, **57 (2)**, 293–305, June 2011), addresses the question of how to account for improvements in labour quality in a growth accounting context and explores a modified skill measure using information from a wage equation. The construction of proper economy-wide indices of labour quality (or human capital) has long been discussed by economists (see for instance Jorgenson *et al.*, 1987). Human capital is the foundation of *knowledge-based capital*, KBC (see OECD, 2013), and recently different attempts have been made to improve measurements of human capital in the context of the *knowledge-based society* pronounced by Europe 2020 (see Dindire, 2012).

A common method used to construct an index of skill-adjusted labour input is to divide the workers into several groups and then let the growth in labour input services be a weighted sum of the increases in man-hours in each of the groups. The simplest way of accounting for labour heterogeneity is to classify workers as high-skilled and low-skilled based on their years of schooling. Another idea is to assume that the relative efficiency of any two workers equals their wage ratio (see Griliches, 1960). Based on this assumption one may calculate efficiency-adjusted man hours. Both methods have obvious shortcomings. While, years of schooling may be a too rough proxy for skill (see the discussion in Borghans *et al.*, 2001); the observed wage differences do not only reflect skill differences, but also variables unrelated to skill, such as regional and temporal variations in labour market conditions, rent sharing, workers' bargaining power, and transient fluctuations. The main idea of this essay is to decompose the worker's wage in two parts: the first part is a function of variables related to the worker's skill (observed and unobserved personal characteristics) and the second part covers variables unrelated to skills.

Next issue when constructing an index of skill-adjusted labour input is the choice of weights. The simplest way to calculate weights is to use the observed mean wages associated with the different groups of workers. An alternative is to employ mean predicted wages from a wage equation. In the current paper we suggest an alternative method for handling heterogeneity of labour within a growth accounting framework. Utilizing a rich employer-employee panel data set on Norwegian firms in eleven manufacturing industries in 1995–2005, we start out by estimating a wage equation for each of the industries. From the estimated wage equation we extract what one may label the skill component of the predicted wage, which solely captures the effects of observed and unobserved individual variables. We then sort these predicted wages in ascending order and divide them into deciles. In each year we then know which decile the worker belongs to and how many man-hours he/she contributes with. This information is used to construct an index of skill-adjusted labour. The change in this index is a weighted average of the change in man-hours for each of the 10 groups. To calculate the weights we use the relative median values of the skill-related predicted wages within each decile.

The estimated wage equations are also utilized in conjunction with a *benchmark method*, where we divide the observations into 12 cells distinguishing between high and low education, three intervals of experience, and gender. For each year we calculate the total number of man-hours and the mean of the predicted (skill related) wages in each of the cells. This information is used to derive an index of labour services. We consider calculation of TFP growth at the industry level when labour is treated in three different ways. In the first case labour is considered a homogeneous input variable. The second case corresponds to what we referred to as the benchmark method, whereas in the third case we calculate TFP growth using the new method suggested in this article. We find that the TFP growth diminishes when one goes from the case with homogeneous labour to the benchmark method and even further when one goes from the benchmark method to the decile-based method proposed in this article. This means that when using the alternative method one explains more of the growth in labour productivity by input factors than what a more traditional labour quality adjustment procedure does.

There are a few other studies that develop an index for the measurement of labour quality growth employing a wage equation approach, i.e. Bolli and Zurlinden (2012) and Lacuesta *et al.* (2011). These contributions focus on robustness issues in different dimensions, i.e. Bolli and Zurlinden (2012) are occupied with the implications of taking account of unobserved worker characteristics, while Lacuesta et al. (2011) have a special focus on selection problems caused by a substantial amount of inflow of immigrant workers to Spain. In our study we also take into account the unobserved personal characteristics when decomposing the worker's wage in two parts: one related to the worker's skill and another one unrelated to skills. However, our approach is highly data-demanding making it difficult to implement it on a broad basis.

The third essay, *The effects of R&D tax credits on patenting and innovations* (written jointly with Ådne Cappelen and Arvid Raknerud, and reprinted from *Research Policy*, **41**, 334–345, March 2012), analyses the effects of SkatteFUNN, a tax-based incentive introduced in Norway in 2002, on the likelihood of innovating and patenting. At present, most of the R&D policy evaluation studies have focused on the first-order effects of fiscal incentives (i.e. their direct effects on R&D investments as measured by the estimated additionality ratio). This paper is one of the few studies that have investigated the second-order effects of tax credits on firms' innovation output (i.e. patenting and new products and processes).

The main data source for our analysis is the *Community Innovation Survey* (CIS). There are two surveys, which are of high interest for us. One, taken in 2001, covers the 3 years period before SkatteFUNN was introduced (1999–2001), and the other one, conducted in 2004, covers the 3 years period exactly after it was introduced (2002–2004). Since about 2/3 of the firms are included in both surveys, we are able to obtain a panel data set from these survey data. Availability of such data allows us to control for firm specific and time invariant components of the gross error term and to deal with the self-selection problem (the firms that apply for an R&D support is not a random sample from the population of all potential applicants) by not only controlling for selection on observables, but also for selection on unobservables.

Our modelling framework is influenced by Griliches (1990), Crepon *et al.* (1998) and Parisi *et al.* (2006). The main idea in this literature is that by investing in R&D, the firm accumulates R&D capital, which plays an important role in its innovation activities. Using binary regression models, we model the probability of innovating and patenting as function of the firm's R&D capital stock at the *beginning* of each three year period, whether it participated in SkatteFUNN or not, and different firm characteristics (size, industry, share of high–skilled workers, etc.). Even if R&D *investments* are simultaneously determined with innovation activities, the timing of our R&D variable allows us to consider the R&D *capital stock* as predetermined. Moreover, access to panel data gives us an opportunity to estimate models that explicitly take into account the *persistence* of innovation activities within firms by conditioning on past innovation and patenting activities. To identify causal effects of

SkatteFUNN, we model the probability of obtaining SkatteFUNN and the probability of innovations simultaneously, while carefully examining the validity of identifying restrictions.

Our results show that the SkatteFUNN scheme contributes to the development of new production processes and, to some extent, to the development of new products for the firm. Firms that collaborate with other firms in their R&D activities are more likely to innovate. However, the scheme does not appear to contribute to innovations in the form of new products for the market or more patenting.

Recent literature reviews, one on micro-econometric evaluation studies conducted by Arvantis (2013), and another one on studies that focus on the effects of R&D tax credits conducted by Castellacci and Lie (2015), identify only two more studies where the dependent variable is innovation output, i.e. Berube and Mohnen (2009) and Czarnitzki *et al.* (2011). The former study compares the impact of incremental R&D tax credits versus R&D grants on innovation output (eight innovation indicators), while the latter focuses on the effects of R&D tax credits on new product performance (number of new products; sales share of new products; introduction of a world or country novelty). Both studies use Canadian data and the propensity score matching method to take into account the self-selection problem. However, this rather standard approach in the evaluation literature (used in 22 out of 38 studies covered by Arvantis, 2013) only controls for selection on observables, while we control for both, i.e. selection on observables and selection on unobservables. To sum up, there exists a relatively large literature evaluating the effects of public R&D subsidy programs on firms' R&D investment (with focus on possible crowding-out effects), while there are still few studies investigating the second-order effects of R&D policies on firms' innovation output. Hence, more evidence is needed.

The fourth essay, *Returns to public R&D grants and subsidies* (written jointly with Ådne Cappelen and Arvid Raknerud), addresses the question of whether the returns to R&D differ between R&D projects funded by public grants and R&D in general. Access to public grants may change a firm's incentives for carrying out R&D in several ways. One way is obviously by reducing the marginal cost of R&D and hence also the required returns. Thus, one may suspect that publicly funded R&D projects have lower private returns than internally funded projects in the absence of the grant. Another way is by improving the liquidity of the firm. In the latter case, the subsidy may finance R&D investments that would have been profitable also in the absence of subsidies (see the third essay and Hall, 2002, for discussions of the importance of financing constraints for R&D investments). In the existing empirical literature, the most common way of estimating returns to R&D is to lump together all R&D spending for each firm or industry (or even country) without distinguishing between sources of finance. Thus, it is implicitly assumed that projects are perfect substitutes and that they have the same economic returns. In this paper, we use a flexible production function that distinguishes between different types of R&D by source of finance.

We investigate the productivity and profitability effects of R&D using a comprehensive panel of Norwegian firms in all industries in 2001−2009. More specifically, we focus on the productivity effects of R&D grants given by the Research Council of Norway as opposed to privately funded R&D. To assess the productivity effects of R&D at the firm level, it is important to allow for the possibility of running a viable firm without ever undertaking R&D. According to the Norwegian R&D surveys, most firms report that they do not undertake any R&D. Nevertheless, the most common approach is to use a Cobb-Douglas function and to estimate the model using only firms with positive R&D (cf. the survey in Hall *et al.*, 2010). This creates a sample selection that may bias the results. Our results, based on a flexible production function that encompasses Cobb-Douglas as a special case, show that the bias may indeed be large. According to our preferred model, R&D projects subsidized by the Research Council of Norway do not differ significantly from R&D spending in general. Our estimate of the average rate of return to R&D is about 10 percent. This estimate is low compared to the rate of return commonly reported in the international literature, cf. Hall *et al.* (2010). However, this estimate is robust with respect to whether firms with zero R&D are included in the estimation sample or not. In contrast, using a standard Cobb-Douglas specification and restricting the sample of firms to those with positive R&D, leads to implausibly high estimates of the rate of returns.

The fifth and final essay, *The innovative input mix: Assessing the importance of R&D and ICT investments for firm performance in manufacturing and services*, examines the firm-level relationships between innovation, productivity and two of their major determinants, namely R&D and Information and Communication Technology (ICT). ICT is one of the most dynamic areas of investment, as well as a very *pervasive* technology.[5] The possible benefits of ICT use to a firm include among others increased input efficiency, general cost reductions and greater flexibility in the production process (see OECD, 2003). This technology can also stimulate innovation activity in a firm, leading to higher product quality and the creation of new products or services. Its use has the potential to increase innovation by improving possibilities for communication and speeding up the diffusion of information through networks. Previous analyses confirm that ICT plays an important role in firm performance, *e.g*. Gago and Rubalcaba (2007), Crespi *et al.* (2007) and van Leeuwen (2008). These studies evaluate the impacts of ICT use and innovation on productivity. A few recent studies, i.e. Hall *et al.* (2013), Vincenzo (2011) and Polder *et al.* (2009), focus on the direct link between ICT and innovation.

In the spirit of Polder *et al.* (2009) and Hall *et al.* (2013), I rely in this paper on an extended version of the CDM model (Crepon *et al.*, 1998), which treats ICT investment together with R&D as two main inputs into innovation and productivity. I use a rich firm-level data set based on the four recent waves of the *Community Innovation Survey* (CIS) for Norway (CIS2004–CIS2010) and test two measures of innovative output, i.e. different types of innovation (product, process, organisational and marketing innovation, or any innovation) and the number of patent applications.

Beyond presenting results for Norway (one of the countries with a high rate of ICT diffusion), this paper contributes to the existing literature in several ways. Firstly, I take into account the *pervasiveness* of ICT and treat it in parallel with R&D as a main input into innovation, rather than simply as an input into the production function. Secondly, in order to account for industry heterogeneity, I provide separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). Thirdly, I include marketing innovation in the analysis in addition to earlier investigated product, process and organisational innovation. All four types of innovation are equally represented in the data, which makes it possible to analyse the whole set of innovation types and enables a better understanding of the innovation process in the firm. Finally, I use the number of patent applications as an alternative measure for innovation. While the combination of different innovation types shows the *variety* of innovative processes in a firm, the number of patent applications reflects the *quality* of the innovation, i.e. only the best innovative products are expected to be protected by patent.

The estimation results indicate considerable differences between firms in manufacturing and service industries with respect to innovation and the productivity effects of R&D and ICT. While ICT investment is strongly associated with all types of innovation in both sectors, with the result being strongest for product innovation in manufacturing and for process innovation in service industries, the impact of ICT on patenting is only positive in manufacturing. The estimation results also confirm that R&D and ICT are both strongly associated with innovation and productivity, with R&D investment being more important for innovation, and ICT investment being more important for productivity. These results suggest that ICT is an important driver of productivity growth and that it, together with R&D and human capital, should be taken into account when studying productivity.

[5] ICT is often referred to as a modern general purpose technology, GPT (see Bresnahan and Trajtenberg, 1995, for a definition of GPT).

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Essay 1:

Lumpy investments, factor adjustments and productivity

Co-authored with Øivind A. Nilsen, Arvid Raknerud and Terje Skjerpen

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Essay 2:

The importance of skill measurement for growth accounting

Co-authored with Øivind A. Nilsen, Arvid Raknerud and Terje Skjerpen

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The importance of skill measurement for growth accounting*

by

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Abstract

In a growth accounting context one usually constructs a quality adjusted index of labor services by aggregating over predefined groups of workers, using the groups' relative wage bills as weights. In this article we suggest a method based on decomposing individual predicted wages into a skill-related part and a part unrelated to skill, where the former consists of both observed and unobserved components. The predicted wages, associated with individual skill attributes, are sorted and classified into deciles. The median predicted skill-related wage in each decile is used to construct an alternative skill-adjusted index of labor services. We find that Total Factor Productivity (TFP) growth decreases significantly when using the latter method. This means that when using the alternative method one explains more of the growth in labor productivity than what a more traditional labor quality adjustment procedure does.

JEL classification: C23, D24, J24, J31
Keywords: TFP growth, Skill measures, Wage equation

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1 Introduction

In the growth accounting literature it has since long been acknowledged that one should pay attention to improvements in labor quality (see for instance Jorgenson *et al.*, 1987, and Bureau of Labor Statistics, 1993). Ignoring the labor quality component when carrying out growth accounting implies that improvements in labor quality are allocated to the residual TFP growth component, which incorporates the contribution of all unobserved production factors and hence is difficult to interpret. The issue of productivity measurement with heterogeneous labor is discussed in OECD (2001, chapter 4.5), Ahmad *et al.* (2003, chapter 4.5) and Boulhol and Turner (2009). These references also provide some recommendations with regard to practical implementation.

The idea behind skill-adjusting labor is based on the fact that labor is not a homogeneous input, but differs in skill and efficiency. If one replaces a worker with a more productive one, assuming that they work the same number of man-hours, an increase in output will, *ceteris paribus*, be the result. The question then is how to measure differences in productivity. An early idea put forward by Griliches (1960) was to look at relative wages. In a perfect labor market wage differences should mirror differences in productivity. The approach pursued in the present paper also builds on this idea, but is modified. We view variation in skill related predicted wages as more informative about variation in productivity than the raw hourly wages. Observed wage differences do not only reflect skill differences, but also variables unrelated to skill, such as regional and temporal variations in labor market conditions, rent sharing, unions' bargaining power, and transient wage fluctuations.

A common method used to construct an index of skill-adjusted labor input is to divide the workers into several groups and then let the growth in labor input services be a weighted sum of the increases in man-hours in each of the groups. As Zoghi (2010) points out one may calculate weights in different ways. The simplest way is to utilize the observed wage bills associated with the different groups. An alternative to using observed mean wages, which may be somewhat volatile, is to employ mean predicted wages from a wage equation. Bolli and Zurlinden (2009), Lacuesta *et al.* (2008) and Schwerdt and Turunen (2007) represent, in a broad sense, recent contributions within this type of approach. These contributions focus on robustness issues in different dimensions. For instance Bolli and Zurlinden (2009) are occupied with the implications of taking account of unobserved worker characteristics, while Lacuesta *et al.* (2008) have a special focus on selection problems caused by a substantial amount of inflow of immigrant workers to Spain.

The main contribution of the current paper is to suggest an alternative method for handling heterogeneity of labor within a growth accounting framework. We start out by estimating a wage equation at the industry level using a panel data model for eleven manufacturing industries. As explanatory variables in the equation we include variables related to individual skill or personal attributes; that is, length of education, experience, type of education and gender. In addition we include dummies for local labor market areas and fixed effects for years. From the estimated wage equation we extract what one may label the skill component of the predicted wage, which solely captures the effects of observed and unobserved individual variables. We then sort these predicted wages in ascending order and divide them into deciles. In each year we then know which decile the worker belongs to and how many man-hours he/she contributes with. This information is used to construct an index of skill-adjusted labor. The change in this index is a weighted average of the change in man-hours for each of the 10 groups. To calculate the weights we use the relative median values of the skill-related predicted wages within each decile.

The estimated wage equations (one for each of the industries) are also utilized in conjunction with a benchmark method, where we divide the observations into 12 cells distinguishing between high and low education, three intervals of experience, and gender. For each year we calculate the total number of man-hours and the mean of the predicted (skill related) wages in each of the cells. This information is used to derive an index of labor services.

We consider calculation of TFP growth at the industry level when labor is treated in three different ways. In the first case labor is considered a homogeneous input variable. The second case corresponds to what we just referred to as the benchmark method, whereas in the third case we calculate TFP growth using the new method put forward in this article. We find that the TFP growth diminishes when one goes from the case with homogeneous labor to the benchmark method and even further when one goes from the benchmark method to the decile-based method proposed in this paper. For the manufacturing industry as a whole the annual mean TFP growth in the sample period is 2.5 percent when labor is treated as a homogeneous input, 2.3 percent when skill is accounted for by the benchmark method and 2.0 percent when using our decile-based method.

The paper proceeds as follows. In Section 2 we describe the data used in our analysis. Section 3 deals with classification of labor according to skill. In Section 4, we calculate growth in total factor productivity (TFP) applying the different ways of measuring labor input. Section 5 concludes the paper.

2 Data

For this study we use a rich employer-employee panel data set on Norwegian firms, covering the period 1995–2005. The sample is based on information from limited dependent companies (i.e., the smallest legal unit). We have constructed panels of annual firm-level data for Norwegian firms in eleven manufacturing industries, accounting for about 90 percent of total man-hours in manufacturing.

Five different sources of Norwegian micro data are used. Two of them are firm-level data sets. One of the firm-level data sets is based on the accounts statistics of limited dependent companies, and the other comprises structural statistics for different industrial activities. These data sources provide information on value-added and capital at the end of the year in constant prices (for details about the capital variable see Raknerud *et al.*, 2007). The three remaining data sets contain individual-level data. These are the Register of Employers and Employees, the Pay Statements Register, and the National Education Database. The individual level data provide us with information on man-hours, wages (constructed as annual earnings at constant prices divided by contracted annual working hours), the worker's place of residence, length and type of education, and potential experience - calculated as a person's age minus the length of his education minus the age at which he/she started at compulsory primary school. This information makes it possible to link firm-level and individual-level information and to integrate individual-level data into a common data base and then aggregate to the firm level.[1]

3 Skill classification

We start out by classifying workers into K different skill categories, according to their relative efficiency. The categories are sorted in ascending order such that the least efficient workers are in category 1, and each category contains the same proportion of total man-hours, i.e., $100/K$ percent. If $M_{(k)t}$ denotes total man-hours in skill category k, for $k = 1, ..., K$, then total man-hours, M_t, can be written as

$$M_t = \sum_{k=1}^{K} M_{(k)t}.$$

A particular set of efficiency weights, λ_k, $k = 1, ..., K$, with $\lambda_{k-1} < \lambda_k$, is applied to the man-hours in each category, k, to calculate efficiency-adjusted aggregate man-hours, $\widetilde{M}_t$:

$$\widetilde{M}_t = \sum_{k=1}^{K} \lambda_k M_{(k)t}, \quad 1 = \lambda_1 < \lambda_2 < ... < \lambda_K, \tag{1}$$

These parameters are calibrated based on the assumption of perfect substitution between workers, such that relative efficiency between a worker in skill category k and 1, λ_k, is equal to their relative wage. Instead of using the actual relative wages between individuals observed in the data to calculate λ_k, we use the skill-related part of the predicted wages, as motivated by the discussion in Section 1.

The following wage equation is estimated separately for each industry (for ease of exposition we suppress the index for industry throughout the paper):

$$\ln(W_{prt}) = Z_{rt}\gamma_z + X_{pt}\gamma_x + \nu_p + \varepsilon_{prt}, \tag{2}$$

where W_{prt} is the hourly wage of person p working in labor market region r in year t. On the right hand side, we specify two (row) vectors with observed variables, Z_{rt} and X_{pt}. The vector of explanatory variables Z_{rt} consists of observed variables that are related to the labor market region (r) where the individual works and the calendar

[1]For a more detailed description of data sources used, see the Data Appendix of Nilsen *et al.* (2009).

year (t), and is assumed to be unrelated to the individual's skill:[2]

$$Z_{rt} = (\text{labor market region dummies, year-specific dummies}).$$

The other vector, X_{pt}, contains values of variables related to individual p's skill in year t:[3]

$$\begin{aligned} X_{pt} &= (\text{years of schooling, powers of years of experience up to 4'th order,} \\ &\quad \text{gender, type of education-dummies}). \end{aligned}$$

The attached coefficient vectors are denoted γ_z and γ_x, respectively. The scalar ν_p is an unobserved individual random effect of individual p. Finally, ε_{prt} denotes a genuine error term.

Next we decompose the log wage, $\ln(W_{prt})$, into three parts:

$$\ln(W_{prt}) = \omega_{pt} + Z_{rt}\gamma_2 + \varepsilon_{prt},$$

where

$$\omega_{pt} \equiv X_{pt}\gamma_1 + \nu_p \tag{3}$$

is the only part which is relevant to skill measurement, while the second part; related to the variables in the vector Z_{rt}, and the third part; the transient noise ε_{prt}, do not concern skill measurement.

To calculate the weights λ_k, and to classify workers into skill categories, only the skill-related part, ω_{pt}, of the wage will be used, cf. (3). The detailed calculations are as follows: Consider all the values of ω_{pt} occurring in our sample and sort them in ascending order. To be specific, assume that $K = 10$ (deciles), which is what we actually use in our application. Then let $\omega_{(1)} < \omega_{(2)} < \cdots < \omega_{(10)}$ denote the 5, 15, 25, ..., 95 percent quantiles in the empirical distribution of ω_{pt}. Thus $\omega_{(k)}$ is the median predicted wage (after removing the effect of noise, ε_{prt}, and labor market region and time dummies, Z_{rt}) within category k. The man-hours of person p at time t are

[2] The definition of the seven labor market region dummies is based on characteristics such as size and centrality (see http://www.ssb.no/english/subjects/06/sos110_en/sos.110_en.pdf).

[3] The data investigation shows that mainly workers with the following three types of education are represented in the chosen industries: education in "General programs", "Business and Administration" and education in "Natural Sciences, Vocational and Technical subjects".

allocated to category k iff

$$k = \arg\min_j |\omega_{pt} - \omega_{(j)}|.$$

Finally, we calibrate the efficiency parameters using the relative median skill-related predicted wages:

$$\lambda_k = \frac{\exp(\omega_{(k)})}{\exp(\omega_{(1)})},\ k = 1, ..., 10. \tag{4}$$

The median $\omega_{(k)}$ is then the middle point within the k'th decile, and is chosen as the reference point as it is not vulnerable to outliers, in contrast to the corresponding mean value of ω_{pt}. In general, the difference between $\omega_{(k)}$ and the mean value of ω_{pt} within the k'th decile is small, except for the highest decile, where the mean is influenced by a few high outliers. Of course, this framework can be used for any K, and the modified definitions of the $\omega_{(k)}$ follow straightforwardly.

In practice, $\omega_{(k)}$ and λ_k must be estimated. This is done by replacing ω_{pt} with

$$\widehat{\omega}_{pt} \equiv X_{pt}\widehat{\gamma}_1 + \widehat{\nu}_p,$$

where $\widehat{\gamma}_1$ denotes the estimated parameter vector and $\widehat{\nu}_p$ is the predicted random effect of individual p based on feasible GLS estimation. In our empirical analysis, the parameters $\omega_{(k)}$ and λ_k are replaced by estimates, $\widehat{\omega}_{(k)}$ and $\widehat{\lambda}_k$, using $\widehat{\omega}_{pt}$ instead of ω_{pt}. The unknown parameters in (2) are estimated by GLS using unbalanced panel data for each industry. The assumption that v_p is a random effect is convenient in order to identify γ_x – in particular the coefficient attached to years of schooling, which in our sample is close to being an individual-specific time-invariant variable.

An objection frequently raised against random effects models is that the GLS-estimators applied to estimate them are biased if the latent effect is correlated with the observed right-hand side variables. However, in our setting there are several problems attached to using fixed effects estimators. First, for a substantial part of the individuals there are too few observations in order to obtain precise estimates. Second, most of the observed right-hand side variables are time-invariant or nearly so, which implies a genuine identification problem. Third, since we apply the wage equations also to predict wages for observations not included when estimating the wage equation (see below) the random effects specification seems more appropriate. In light of these three features we have chosen to stick to the random effects specification instead of the fixed effects specification.

Before we estimate the wage equation (2), we carry out some data cleaning. First, since wages of part time workers are particularly hampered by measurement errors, we omit data for part-time workers. Second, we omit wage observations which are viewed as being either unusually high or unusually low. The corresponding cut-off values are obtained using quantile regressions. For each industry, we perform quantile regressions for the 5 and 95 percent quantiles, respectively, to estimate these quantiles conditional on labor market region and calendar year (which are the only included regressors). When estimating the wage equations, we omit observations that are characterized by either hourly wages below the conditional 5 percent or above the conditional 95 percent quantiles. This procedure ensures smoother quantiles across time and labor market region compared to the raw data quantiles.

[Table 1: Wage equation estimation results]

The data cleaning referred to above has been done only when estimating the wage equation. The omitted observations are included again when performing the final TFP calculations. Based on the wage equations we predict the skill-related wages for all persons in every period they are observed. For workers not included in the estimation sample, we obtain $\widehat{\omega}_{pt}$ by using the observed X_{pt} and setting $\widehat{\nu}_p = 0$, which is the optimal *ex ante* estimate of the random effect.

The results from the wage equation estimations are reported in Table **??**. We see that the marginal returns to education are approximately 5 percent, in line with other studies based on Norwegian data (see for instance Hægeland *et al.*, 1999). The coefficients attached to years of experience are hard to interpret directly, since the effect of experience is represented by a fourth order polynomial. If we only look at the first order term, we find returns of the same magnitude as for education. However, the marginal returns to experience is decreasing and becomes zero at around 30–32 years of experience, and negative thereafter. The effects of the other explanatory variables, such as gender, labor market region and type-of-education are all in line with our prior expectations.

[Figure 1: The efficiency parameters in different industries]

The calculated values of λ_k for all the manufacturing industries are displayed in Figure 1. We see that there is considerable variation in λ_k across the different industries, for a given decile k. In particular, λ_{10} is highest in the typical high-tech industry Electrical equipment (which also have the highest share of workers with at least 13 years of education; about 35 percent), especially compared to the traditional low-tech industry Wood products (where the share of workers with at least 13 years of education is about 8 percent). One also notes that the curves of Electrical equipment and Chemical products are steeper at the upper part of the distribution compared to industries characterized by a large share of low-skilled workers. Thus the high-tech industries seem to employ and reward workers with especially high productivity.

We will consider different types of benchmark methods for calculating efficiency weighted total man-hours, $\widetilde{M_t}$. A trivial benchmark is, of course, to set $\widetilde{M_t} = M_t$, i.e., no skill adjustments. In the (more elaborate) benchmark method we will classify workers (or man-hours by a particular worker in a given year) into cells based on values of a sub-set of the covariates, X_{pt}, described above. Then we follow Zoghi (2010) and skill-adjust the change in input of labor services by calculating the change in a Törnqvist index. The weight of the workers in cell j, $j \in J$, is the skill-related wage bill for this group of workers divided by the total skill-related wage bills for all the groups. In our application we will consider a case with 12 cells. The classification is based on three variables: Education length, Experience and Gender, where Education length has two discrete outcomes: less than 13 years and at least 13 years, and Experience has three disjunct outcomes: Experience ≤ 7 years; $8 \leq$Experience ≤ 15 years; Experience ≥ 16 years. A listing of the cells with definitions is given in Table A.2 in the Appendix.

4 Productivity growth analysis

To analyse the importance of the choice of different skill measures, we consider a growth accounting framework at the industry level implicitly assuming constant returns to scale. Instead of sticking to a Cobb-Douglas production function specification with constant share-parameters, we allow for time-varying share-parameters and employ Törnqvist indices. As pointed out by Morrison Paul (1999, p. 43) and Diewert

(1976) this choice is consistent with assuming a translog production function. The growth in labor productivity, $\Delta \ln(Y_t/M_t)$, where Y_t and M_t are valued added and the total number of man-hours at the industry level, respectively, is decomposed into contributions from heterogeneous labor (to be specified below), capital services, K_t, and a residual term, ΔTFP_t. The latter denotes growth in total factor productivity.[4] The expression for the relative growth in labor productivity is given by

$$\Delta \ln\left(\frac{Y_t}{M_t}\right) = \alpha_t \Delta \ln\left(\frac{\widetilde{M}_t}{M_t}\right) + (1-\alpha_t)\Delta \ln\left(\frac{K_t}{M_t}\right) + \Delta TFP_t, \tag{5}$$

where $\widetilde{M}_t$ is aggregate skill-adjusted man-hours according to our proposed method, as defined in (1) or calculated according to the benchmark method. Equivalently, we can write

$$\Delta TFP_t = \Delta \ln\left(\frac{Y_t}{\widetilde{M}_t}\right) - (1-\alpha_t)\Delta \ln\left(\frac{K_t}{\widetilde{M}_t}\right).$$

Using the benchmark method, we follow Zoghi (2010), and define

$$\Delta \ln(\widetilde{M}_t) = \sum_{j\in J} 0.5(s_{jt} + s_{j,t-1})\Delta \ln(M_{jt}), \tag{6}$$

where M_{jt} is the number of man-hours in cell j at time t, and the s_{jt} are weights defined as follows:

$$s_{jt} = \frac{\exp(\widehat{\omega}_{jt})M_{jt}}{\sum_{j\in J}\exp(\widehat{\omega}_{jt})M_{jt}},$$

where $\widehat{\omega}_{jt}$ denotes the mean value of $\widehat{\omega}_{pt}$ belonging to cell j in year t, cf. (3). Following the traditional approach in growth accounting, the industry level share-parameter α_t is calibrated using the arithmetic mean of the cost share of labor (i.e., the total wage bill divided by total factor costs) in period t and $t-1$.[5]

For each industry in the manufacturing sector, we compare the TFP growth obtained from (5) with two other cases: First, when $\lambda_k \equiv 1$ for all k and hence $\widetilde{M}_t$ in (5) is replaced by the non-adjusted man-hours, M_t, and second, when $\Delta \ln(\widetilde{M}_t)$ is calculated as in (6) based on an index set, J, consisting of 12 categories. Note that the left-hand side of (5) does not depend on the skill measure used, since M_t equals total man-hours.

[4] In the TFP growth calculations we only include firms with at least three years of contiguous data and no missing variables.

[5] In the current paper we do not consider the link between TFP growth at the plant/firm and the industry levels, as discussed in Hulten (2001, pp. 38–39). Cf. also Baily *et al.* (1992) and Foster *et al.* (2001).

[Table 2: Growth equation estimates]

We see from the results reported in Table 2 that labor costs as a share of total factor costs are approximately 70 percent on average, but vary considerably, from about 80 percent in Electrical equipment and Transport and communication to about 50 percent in Mineral products. Furthermore, labor productivity growth (3.5 percent annually, averaging over all the industries) is mainly explained by capital deepening. Growth in labor quality also contributes: Regardless of which method is used to skill-adjust labor input, the growth in skill-adjusted man-hours is higher than the growth in number of man-hours (i.e., $\Delta \ln \left(\widetilde{M}_t / M_t\right)$ is positive in all industries). The lower value of TFP-growth using our method compared to the benchmark method is solely accounted for by a higher growth in skill-adjusted man-hours obtained with our method.

In Table 2 we also report the mean annual growth in labor productivity over the period 1995–2005 together with the mean annual TFP growth according to (i) the case without any skill adjustment, (ii) the benchmark method, and (iii) the new wage equation based skill-adjusted measure of labor input put forward in this paper.

With no skill adjustment, the mean annual TFP growth varies between 0.5 and 3.7 percent, with 2.5 as an average across the industries. Our proposed effi ciency adjustment leads to an even wider difference. The latter difference varies from less than 0.1 percentage point to 0.4 percentage points. On average, our method leads to 0.5 percentage points lower TFP growth than the case with no quality adjustment, and 0.3 percentage points lower growth compared to the benchmark method. Thus, our method unambigously leads to reduced TFP growth, by allowing more of the change in value-added to be picked up by the measurable components compared to the benchmark method.

We have considered some robustness checks. First, we have added type of education as an extra dimension for the benchmark method. This variable has three outcomes: General programs; Vocational and technical subjects; and Other type of education. Thus, the benchmark method now involves 48 cells. We find for all industries that the TFP growth for this extended version of the benchmark method is practically indistinguishable to the one obtained for the benchmark method using 12 cells. This resembles the conclusion obtained by Fosgerau *et al.* (2002) using Danish data. As second robustness issue we have investigated how sensitive the results are with respect to the cut-off values used when trimming the data set for the full time workers. Instead of applying the thresholds corresponding to the 5 and 95 percent conditional quantiles, we have employed the 1 and 99 percent thresholds. It turns out that even though the estimates of the parameters in the wage equations are somewhat changed, the predicted values obtained from the estimated wage equations are very similar. Accordingly, the estimated TFP growth is not significantly influenced by the application of these alternative cut-off values.

As a last robustness check we have tested whether it is the effect of a decile-based classification or the effect of using only the skill-related part of the predicted wages that drives the differences in TFP growth. We do this by calculating the TFP growth using two 'naïve' decile-based methods based on; a) actual wages and b) detrended actual wages, i.e., no skill-correction of wages. The method a) almost completely eliminates TFP-growth. Wages (as well as labor productivity) have a positive time trend. Thus, over time an increasing part of the man-hours will be classified in the higher deciles. Without removing this trend before applying the decile-based method, we could end up with a situation where all man-hours found in the lowest deciles were from the early sample years, while the man-hours in the upper deciles were all coming from the last years. Ignoring the positive trend for both wages and productivity implies that one will be exposed to what is known as "spurious regression" in the time series literature. To avoid spurious results, we therefore applied method b) in order to remove the time trend from the actual wages before applying the decile-based method. We now obtain TFP growth rates that are almost identical to those of the benchmark (1) reported in Table 2 (without any skill-adjustment of man-hours). From these two tests we conclude that including only the skill-related predicted wages (removing e.g. the unexplained time trend) is crucial for the decile-based method to be both economically sound and empirically successful.

Why does our method for skill adjustment yield a higher increase in labor quality growth than what is obtained using the benchmark method? We have seen that this has nothing to do with the number of cells used in connection with the benchmark method. There are two main differences between the methods that may explain the difference in labor quality growth. First, a person-specific unobserved effect is included in the skill-related part of the wage equation. Hence the categorization of persons into effi ciency deciles partly reflects an unobserved component which plays no role in the benchmark method. Second, it is an empirical fact that the probability that an individual moves to another decile is larger than the probability that he/she moves to another cell (see Table A.3 and Table A.4 in the Appendix, which show transition rates between deciles and cells of the benchmark, respectively). Note that transitions from one decile to another are caused by changes in the skill-related variables occurring in the wage equation, most importantly experience.[6] The decrease in the (residual) TFP-growth term when switching from the benchmark method to our decile-based method shows that the increased variability in skill-adjusted man-hours using the latter method instead of the former method enables us to explain labor productivity growth in a better way.

A final important question is whether the differences in the mean TFP growth using the various skill measures are statistically significant. To answer this question we provide standard errors of the mean difference in TFP growth by means of bootstrapping. The bootstrap works as follows. From the dataset used to produce the TFP growth estimates reported in Table 2 we draw a sample of N firms (with replacement). For each of these N firms we use the entire time series of output, wage costs, hours of work, and capital. In each replication we calculate the difference between the mean TFP growth obtained using our decile-based method and the benchmark method. After 250 bootstrap replications, we calculate the standard deviation of the differences in mean TFP growth over the bootstrap sample and take this as an estimate of the standard error of the difference in mean TFP growth. We find that the difference in estimated TFP growth between the quantile-based method and the benchmark method is statistically significant (the estimated standard error of the difference equals 0.09 percentage points). If we now consider a 50-years horizon as an example, which is not uncommon in long-run projections, a constant annual TFP growth rate of 2.0 instead of 2.3 percent implies a 42 percentage point lower TFP growth over such a time span. Thus, an improved measure of labor input has non-negligible effects when considering

[6]Note that this mobility has nothing to do with a general positive trend in wages, since this trend is captured by the time dummies of the wage equation, which are not included in the quality index.

growth accounting in the long term.

5 Concluding remarks

In this paper we have proposed a new method for constructing an index of labor services. Extracting and classifying skill-related predicted wages plays a decisive role in our quantile (decile)-based method. We calculate the growth of TFP for 11 manufacturing industries using this new measure of labor services and compare the results with what is obtained using (i) a more traditional method for accounting for labor heterogeneity within a growth accounting framework and (ii) assuming homogeneous labor. We find that the new method gives a lower growth in TFP than both (i) and (ii). For the manufacturing sector as a whole we find that the mean annual growth in TFP is 0.3 percentage points lower using the new measure of labor services instead of the more traditional measure (i) based on a set of predefined cells, which we have exemplified by dividing the observations into 12 cells according to length of education, working experience and gender. This can be interpreted as the measure put forward in this paper captures more of the growth in labor quality than the more traditional measure.

While our main concern in the present paper has been to assess the importance of skill adjustment for calculating growth in TFP, elaborations of our approach should be of interest, given the importance of the issue discussed. Perhaps the most natural one is to extend the information set used in the estimation of the wage equations with firm-specific variables, e.g. represented by dummy variables of firms such as in Abowd *et al.* (1999). Another relevant topic is to relax the constant returns to scale restriction when decomposing the growth in labor productivity.

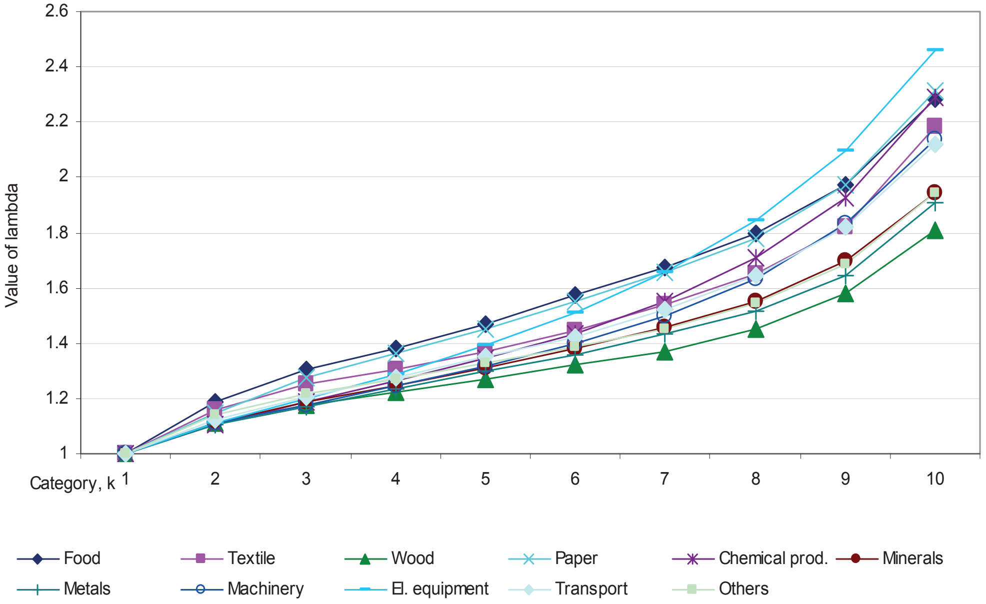

Figure 1: Estimated efficiency parameters, λ_k, for different industries

Table 1: **Wage equation estimation results**

Industry	Educ.	Experience				Gender	Educ. type			No. of	No. of
	length	1. power	2. power$^{a)}$	3. power$^{b)}$	4. power$^{c)}$	Male	Gen.	BA	Sci.&Tech.	ind.	obs.
Food etc.	0.046	0.056	–0.029	0.007	–0.006	0.221	0.044	0.044	0.035	71,721	328,564
	(0.0005)	(0.0007)	(0.0005)	(0.0002)	(0.0005)	(0.0018)	(0.0022)	(0.0026)	(0.0020)		
Textile etc.	0.035	0.036	–0.018	0.004	–0.004	0.239	0.046	0.077	0.036	10,147	44,066
	(0.0015)	(0.0026)	(0.0018)	(0.0005)	(0.0005)	(0.0050)	(0.0063)	(0.0073)	(0.0063)		
Wood etc.	0.036	0.040	–0.020	0.005	–0.044	0.106	0.050	0.059	0.027	22,183	106,570
	(0.0008)	(0.0010)	(0.0008)	(0.0002)	(0.0002)	(0.0038)	(0.0038)	(0.0046)	(0.0033)		
Paper etc.	0.038	0.049	–0.023	0.005	–0.004	0.156	0.027	0.016	0.021	48,759	253,708
	(0.0005)	(0.0007)	(0.0006)	(0.0002)	(0.0002)	(0.0021)	(0.0027)	(0.0027)	(0.0023)		
Chemical etc.	0.060	0.043	–0.018	0.004	–0.003	0.131	0.043	0.032	0.010	36,059	181,448
	(0.0004)	(0.0007)	(0.0005)	(0.0002)	(0.0002)	(0.0025)	(0.0031)	(0.0034)	(0.0027)		
Min. products	0.041	0.039	–0.017	0.004	–0.003	0.155	0.056	0.048	0.039	14,755	71,476
	(0.0008)	(0.0013)	(0.0010)	(0.0003)	(0.0003)	(0.0045)	(0.0042)	(0.0052)	(0.0038)		
Met. products	0.048	0.045	–0.022	0.005	–0.004	0.112	0.056	0.039	0.029	51,666	252,227
	(0.0005)	(0.0006)	(0.0005)	(0.0001)	(0.0001)	(0.0027)	(0.0029)	(0.0035)	(0.0026)		
Machinery	0.056	0.048	–0.023	0.005	–0.005	0.174	0.070	0.047	0.029	38,791	173,249
	(0.0005)	(0.0008)	(0.0006)	(0.0002)	(0.0002)	(0.0034)	(0.0040)	(0.0046)	(0.0035)		
El. equip.	0.064	0.048	–0.019	0.004	–0.003	0.201	0.065	0.051	0.034	33,597	154,983
	(0.0005)	(0.0008)	(0.0006)	(0.0002)	(0.0002)	(0.0028)	(0.0036)	(0.0040)	(0.0032)		
Transport etc.	0.055	0.053	–0.027	0.006	–0.006	0.163	0.082	0.047	0.042	65,534	275,895
	(0.0004)	(0.0007)	(0.0005)	(0.0002)	(0.0002)	(0.0028)	(0.0033)	(0.0039)	(0.0028)		
Furniture etc.	0.038	0.045	–0.023	0.006	–0.005	0.135	0.053	0.076	0.024	20,893	93,538
	(0.0009)	(0.0012)	(0.0009)	(0.0003)	(0.0003)	(0.0034)	(0.0043)	(0.0049)	(0.0039)		

Note: For full industry names and NACE codes see Table A.1. For full names of education types see Footnote 3.
Standard errors in parentheses. A constant term, year dummies and regional labor market dummies are also included as regressors in the wage equation, but the estimated coefficients attached to these variables are not reported in the table.

$^{a)}$The estimated values and standard errors have been rescaled with a multiplicative factor of 10.

$^{b)}$The estimated values and standard errors have been rescaled with a multiplicative factor of 100.

$^{c)}$The estimated values and standard errors have been rescaled with a multiplicative factor of 10,000.

Table 2: **Growth equation results**

Industry[a)]	Labor prod growth	Labor share	Labor quality growth		Capital	TFP growth (%)		
	$100 \times \Delta \ln(Y_t/M_t)$		$100 \times \Delta \ln(\widetilde{M_t}/M)$		$100 \times \Delta \ln(K/M)$			
		α	Benchmark method	Our method		(1)	(2)	(3)
Food etc.	2.8	0.69	0.3	0.6	3.1	1.8	1.6	1.4
Textile etc.	4.4	0.77	0.6	1.1	6.2	3.0	2.6	2.2
Wood etc.	4.0	0.75	0.2	0.4	3.4	3.1	3.0	2.9
Paper etc.	1.5	0.75	0.3	0.3	2.3	0.9	0.7	0.7
Chemical etc.	2.4	0.70	0.2	0.3	2.4	1.7	1.6	1.5
Min. products	0.8	0.50	0.1	0.4	0.7	0.5	0.4	0.3
Met. products	5.6	0.61	0.1	0.3	5.4	3.4	3.3	3.2
Machinery	3.6	0.76	0.3	0.6	4.8	2.6	2.3	2.1
El. equip.	4.9	0.80	0.5	1.0	5.8	3.7	3.3	2.9
Transport	4.8	0.80	1.0	1.5	4.7	3.7	3.3	2.9
Furniture etc.	3.8	0.77	0.2	0.5	4.2	2.8	2.7	2.4
Weighted average[b)]	3.5	0.72	0.3	0.7	3.9	2.5	2.3	2.0

[a)] For full industry names and NACE codes see Table A.1.

[b)] The weights are based on value added.

Note: All figures are simple means of annual growth rates of different productivity variables over the period 1995–2005. The TFP growth is calculated using Eq. (5), with different skill measures; the case with no skill adjustment in column (1), the benchmark method in column (2), and our decile-based method in column (3).

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Appendix: Supplementary tables

Table A.1: **Industries and NACE codes**

Industry	NACE codes	Abbreviated industry label
Food, beverages and tobacco	15-16	Food etc.
Textile and leather products	17-19	Textile etc.
Wood and wood products	20	Wood etc.
Paper and publishing	22	Paper etc.
Chemical and plastic products	25	Chemical etc.
Mineral products	26	Min. products
Metal products	27-28	Met. products
Machinery	29	Machinery
Electrical equipment	30-33	El. equip.
Transport and communication	34-35	Transport etc.
Furniture and others	36-37	Furniture etc.

Table A.2: **Listing of cells for the benchmark method**

Cell	Length of education	Experience	Gender
I	$<$13 years	Experience $<$ 7 years	Male
II	$<$13 years	Experience $<$ 7 years	Female
III	$<$13 years	8 years $\leq$ Experience $<$ 15 years	Male
IV	$<$13 years	8 years $\leq$ Experience $<$ 15 years	Female
V	$<$13 years	Experience $\geq$ 16 years	Male
VI	$<$13 years	Experience $\geq$ 16 years	Female
VII	$\geq$13 years	Experience $<$ 7 years	Male
VIII	$\geq$13 years	Experience $<$ 7 years	Female
IX	$\geq$13 years	8 years $\leq$ Experience $<$ 15 years	Male
X	$\geq$13 years	8 years $\leq$ Experience $<$ 15 years	Female
XI	$\geq$13 years	Experience $\geq$ 16 years	Male
XII	$\geq$13 years	Experience $\geq$ 16 years	Female

Table A.3: Transition rates between different labor quality deciles

	Deciles									
Deciles	1	2	3	4	5	6	7	8	9	10
1	0.84	0.16								
2	0.01	0.81	0.18							
3		0.02	0.79	0.19						
4			0.03	0.80	0.17					
5				0.02	0.81	0.17				
6					0.02	0.84	0.14			
7						0.02	0.87	0.11		
8							0.01	0.91	0.08	
9								0.01	0.95	0.05
10									0.01	0.99

Table A.4: Transition rates between cells for the benchmark method*

	Cells											
Cells	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
I	0.84		0.14				0.02					
II		0.84		0.12				0.04				
III			0.86		0.14							
IV				0.85		0.15						
V					1.00							
VI						1.00						
VII							0.85		0.15			
VIII								0.86		0.14		
IX									0.88		0.12	
X										0.89		0.11
XI											1.00	
XII												1.00

*See Table A.2 for definitions of the cells.

Essay 3:

The effects of R&D tax credits on patenting and innovations

Co-authored with Ådne Cappelen and Arvid Raknerud

Published in the *Research Policy*, **41**, 334–345, 2012

Essay 4:

Returns to public R&D grants and subsidies

Co-authored with Ådne Cappelen and Arvid Raknerud

Returns to public R&D grants and subsidies*

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May 14, 2013

Abstract: We address the question of whether the returns to R&D differ between R&D projects funded by public grants and R&D in general. To answer this question, we use a flexible production function that distinguishes between different types of R&D by source of finance. Our approach requires no adjustment of the sample or data in order to include firms that never invest in R&D, in contrast to the standard Cobb-Douglas production specification. We investigate the productivity and profitability effects of R&D using a comprehensive panel of Norwegian firms over the period 2001–2009. The results suggest that the returns to R&D projects subsidized by RCN do not differ significantly from R&D spending in general. Our estimate of the average rate of return to R&D is about 10 percent. This estimate is robust with respect to whether firms with zero R&D are included in the estimation sample or not. In contrast, using a standard Cobb-Douglas specification and restricting the sample of firms to those with positive R&D, leads to implausibly high estimates of the rate of returns.

JEL classification: C33, C52, D24, O38
Keywords: returns to R&D, public grants, public subsidies, productivity

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1 Introduction

Both economic theory and empirical evidence support the view that R&D plays an important role in raising productivity. The social returns to R&D investment is often found to be higher than the private returns to the investing firm. Thus, in the presence of market failure, policy intervention may be justified if a well-designed intervention scheme can be implemented. R&D incentives are designed in many different ways. Many countries offer tax credit schemes for R&D expenses and all countries in the OECD offer fiscal incentives in the form of grants to R&D. Although more countries have introduced tax incentives over time, there is no consensus on what is best practice. Evaluation of the incentives in various countries may provide some evidence on which policies or policy mixes work well.

Access to public grants may change a firm's incentives for carrying out R&D in several ways. One way is obviously by reducing the marginal cost of R&D and hence also the required returns. Thus, one may suspect that publicly funded R&D projects have lower private returns than internally funded projects in the absence of the grant. Another way is by improving the liquidity of the firm. In the latter case, the subsidy may finance R&D investments that would have been profitable also in the absence of subsidies (see Hall, 2002, and Cappelen et al., 2012, for discussions of the importance of financing constraints for R&D investments). The fact that there are arguments that publicly funded projects should have lower returns than privately funded R&D, but also for the opposite case, warrants a closer empirical investigation.

In the existing empirical literature, the most common way of estimating returns to R&D is to lump together all R&D spending for each firm or industry (or even country) without distinguishing between sources of finance. Thus, it is implicitly assumed that projects are perfect substitutes and have the same economic returns. A more flexible approach allows various projects to be perfect substitutes in terms of economic returns, but without imposing this as an a priori restriction.

In this study we analyze a panel of Norwegian firms in all industries from 2001 to 2009 and focus on the productivity effects of R&D grants given by the research Council of Norway (RCN) as opposed to privately funded R&D. To assess the productivity effects of R&D at the firm level, it is important to allow for the possibility of running a viable firm without ever undertaking R&D.[1] According to the Norwegian R&D surveys, most firms report that they do not undertake any R&D. Nevertheless, the most common way of specifying the underlying production function in the literature is to use a Cobb–Douglas function with R&D capital as a separate production factor (cf. the survey in Hall et al., 2010), which does not fulfill this requirement. The standard approach is to estimate the model using only firms with positive R&D. This creates a sample selection that may bias the results. Our results, based on a flexible production function that encompasses Cobb–Douglas as a special case, show that the bias may indeed be large.

According to our preferred model, R&D projects subsidized by the RCN do not have lower returns than R&D in general. To be more precise, we cannot reject the hypothesis that the productivity effects of RCN-funded projects are similar to that of ordinary R&D. Our estimate of the average rate of return to R&D spending by Norwegian firms is 10 percent. This estimate is low compared to the rate of return commonly observed in the international literature, cf. Hall et al. (2010).

The structure of the paper is as follows. Section 2 presents some studies relevant to our investigation. Section 3 describes our theoretical framework for analyzing the effect of R&D on productivity. Section 4 shows how the variables are constructed from various data sources, Section 5 presents the results and Section 6 offers some concluding comments.

2 Approaches to studying the relation between R&D and productivity

Several models of the relationship between R&D investment and productivity at the firm level have been proposed in the empirical literature. One general model structure was proposed in Pakes and Griliches (1984), was used in Crepon, Duguet and Mairesse (1998), and is usually referred to as the CDM model. Here firm output

[1]The proportion of firms reporting positive R&D in the survey varies from 25 percent to 37 percent during 2001–2009 with about 72 percent of firms never undertaking R&D. For firms with more than 50 employees, the corresponding shares vary from 37 percent to 48 percent with about 49 percent of these firms never undertaking R&D in 2001–2009.

is a function of input services and total factor productivity. Under the assumption of a standard neoclassical production function with constant returns to scale, labor productivity (net value added per man-hour) can be expressed as a function of capital intensity (capital per man-hour), K/L, and total factor productivity, A^*:

$$Y/L = A^* f(K/L). \tag{1}$$

The productivity level, A^*, in (1) is assumed to depend on several variables relating to R&D, market factors, industry, and possibly other variables. One way of specifying this model is to include an intangible factor – "knowledge capital" – explicitly in equation (1) to capture the effect of factors both internal and external to the firm (see the survey by Hall et al., 2010). In the CDM framework, R&D investment is not directly treated as the driving force of productivity, but is instead assumed to influence the productivity level – A^* in equation (1) – through product and process innovations. An extension of this model is found in Hall et al. (2012) where ICT investment is also included. A separate strand of literature looks at the impact of R&D expenditures on innovation separately, cf. Mairesse and Mohnen (2004), or Cappelen et al. (2012).

A common approach when specifying the effects of R&D on productivity is to link the productivity factor A^* in equation (1) to the R&D knowledge stock, R, by assuming that

$$A^* = AR^{\eta}, \tag{2}$$

where η is the elasticity of Y with respect to R, A is total factor productivity and the knowledge capital stock, R, accumulates according to

$$R_t = (1-\delta)R_{t-1} + \widetilde{R}_{t-1}, \tag{3}$$

where δ is the depreciation rate of the knowledge stock and $\widetilde{R}$ is (real) R&D investment. If we assume the depreciation rate to be small, we can write

$$\Delta \ln(A_t^*) = \varrho(\widetilde{R}_{t-1}/Y_{t-1}) + \Delta a_t, \tag{4}$$

where ϱ is the rate of return to R&D, cf. Griffith et al. (2004), and $a_t = \ln A_t$. Equation (4) says that the growth rate of productivity depends linearly on R&D

investment divided by net value added, lagged one year. On the other hand, if an estimate (or qualified guess) of the depreciation rate is available, one can calculate the R&D capital stock, R, using (3), and estimate (1)-(2) directly. Unfortunately, little is known about the depreciation rate of R&D, although 0.15 is a value often encountered in the literature (see Hall et al., 2010). If one is uncertain about the depreciation rate of R&D, but is willing to assume that it is close to zero, model (4) is an alternative. Both approaches are well worth pursuing in empirical work.

Using Italian data, Parisi et al. (2006) estimate the rate of return to knowledge capital to be 4 percent. This is rather low, but is an interesting result for a country with a relatively low R&D intensity in the business sector. Their results show that when both R&D intensity and an indicator for process innovation are included in the model, the R&D variable becomes insignificant. However, this result could be due to a simultaneity problem between R&D and innovation. In addressing this problem, Hall et al. (2012) found much higher returns to R&D for Italian firms.

There are few econometric studies using Norwegian firm data to estimate the rate of return to R&D at the micro level. Klette and Johansen (1998) estimate a model where the knowledge stock accumulates according to a log-linear process. Their assumption is based on the idea that old capital and investment in new knowledge capital are complementary, and therefore the more existing knowledge you have, the higher is the marginal return to investment. They estimate the rate of depreciation to be around 0.15 by imposing some identifying restrictions (no increasing returns to knowledge production). Their estimated mean net rate of return varies considerably across industries, with a mean value of 9 percent.

Griffith et al. (2004) develop a generalization of the model leading to equation (4). Based on theories of endogenous innovation and growth, technology transfer is seen as a source of productivity growth for countries or industries behind the technological frontier. Furthermore, R&D activities are seen as an important factor in creating an absorptive capacity for new knowledge and technology in line with the seminal paper by Cohen and Levinthal (1989). The specification chosen by Griffith et al. (2004) is

$$\Delta \ln (A_t^*) = \varrho \frac{\widetilde{R}_{t-1}}{Y_{t-1}} + \beta X_t + \mu \ln(\frac{A_{F,t-1}}{A_{t-1}}) + \kappa \frac{\widetilde{R}_{t-1}}{Y_{t-1}} \ln(\frac{A_{F,t-1}}{A_{t-1}}), \quad (5)$$

where A_F is the productivity level at the frontier (country or industry). The ratio A_F/A measures the distance to the technology frontier for each firm, and can be seen as a way of capturing "catch-up" effects. The last term on the right-hand side of (5) captures the interaction between the distance from the frontier and R&D intensity, $\widetilde{R}/Y$. The idea is that the further a firm/industry/country lags behind the frontier, the more it will benefit from investing in capacity to learn from or imitate others. Griffith et al. (2004) find that the technology gap variable, or "catch-up" variable, is not significant when entered alone ($\mu = 0$), whereas all the other terms enter significantly. Their conclusion is that disregarding the interaction term in (5) may lead to a potential misspecification, and hence produce a bias when estimating the effects of R&D investments on productivity growth.

An important feature of the (standard) approach is that the production function framework cannot be applied to all firms without modifications, as it predicts zero output for firms with zero R&D. In the literature using micro data, there are several options available to circumvent that problem. One "solution" is simply to study those firms that report positive R&D and neglect other firms. This strategy definitely creates a sample selection problem that may bias estimates of the returns to R&D, because selection depends on the *level* of R&D. The problem of sample selection can be solved ad hoc by adding a small amount of R&D investment to firms with zero reported R&D, which makes it technically possible to include them in the analysis. A refinement of this solution is suggested by Griffith et al. (2006) and Hall et al. (2012). Relying on the CDM approach, they replace observed R&D spending with imputed R&D using data for all firms. In this way, zero R&D investment is replaced by nonzero imputed R&D. While this approach may perhaps be justified for firms who report zero R&D in *some* years, it is clearly speculative to do so for the large proportion of firms (almost 50 percent in our sample) that *consistently* report zero R&D spending over time. For these firms, it is not justified to dismiss zero R&D as a mere measurement error. Finally, one may specify a more flexible functional form that allows zero R&D, as suggested already by Griliches (1979).

The advantage of this solution is that one avoids altering the data or the sample. This is the approach favored in the current paper.

3 Theoretical framework

Our starting point is a production function that is homogeneous of degree one in number of man-hours (L), real capital (K), and a measure of aggregate R&D capital (F). We assume

$$Y = AL^{\beta_0}K^{\beta_1}(\lambda L + F)^{\beta_2}, \tag{6}$$

where Y is production measured as net value added, i.e., net of depreciation, in constant prices, A is total factor productivity (unexplained "efficiency"), and F is an aggregate of two types of R&D capital, N and O;

$$F = (\alpha N^{\rho} + O^{\rho})^{\frac{1}{\rho}}. \tag{7}$$

In (7) we distinguish between RCN-funded R&D capital, N, and other R&D capital, $O = R - N$. N is obtained by using (3) with R and $\widetilde{R}$ replaced by N and $\widetilde{N}$, respectively. Note that the elasticity of substitution between the two types of R&D capital equals $s = 1/(1-\rho)$. If the distribution parameter $\alpha \neq 1$, N and O enter the aggregate *asymmetrically* with N being less productive (for given N and O), then α is lower. In particular, the marginal product of N is higher than that of O when $N/O < \alpha^s$. The special case $s = \infty$ ($\rho = 1$) is particularly important. Then $\alpha = 1$ implies that the two types of R&D capital have the same marginal productivity, whereas $\alpha < 1$ implies that the *lower* the share of RCN finance, the higher the marginal product of R&D. Note that F differs from R unless $s = \infty$ and $\alpha = 1$.

The specification (6), unlike (2), allows the (aggregate) R&D variable, F, to be zero without implying $Y = 0$. Two limiting cases are of particular interest: (i) $\lambda \to 0$, in which case (6) approaches a Cobb–Douglas production function in L, K, and F, and (ii) $\lambda \to \infty$, which we will analyze in more detail below. Note that the model is invariant with respect to choice of scale.[2]

[2]For example, replacing F by $F^* = F/k$, gives

$$Y = AL^{\beta_0}K^{\beta_1}(\lambda L + kF^*)^{\beta_2} = k^{\beta_2}AL^{\beta_0}K^{\beta_1}(\frac{\lambda}{k}L + F^*)^{\beta_2} = A^*L^{\beta_0}K^{\beta_1}(\lambda^*L + F^*)^{\beta_2}$$

, which has the same form as (6).

We argued in the Introduction that RCN-funded projects may have either higher or lower returns than privately funded R&D. Thus our conjecture is that the decomposition of R into N and O, i.e., the ratio N/O, may not matter much for the marginal productivity of R&D. Hence our null hypothesis is that $s = \infty$ *and* $\alpha = 1$. Our alternative hypothesis is that $\alpha \neq 1$.

Assuming $\beta_0 + \beta_1 + \beta_2 = 1$ (constant returns to scale), it follows from (6) that

$$\frac{Y}{L} = A\left(\frac{K}{L}\right)^{\beta_1}\left(\lambda + \frac{F}{L}\right)^{\beta_2}. \tag{8}$$

Taking logarithms of both sides of (8) and reformulating, we obtain

$$y = a + \beta_1 k + \beta_2 \ln\left(\lambda + f\right), \tag{9}$$

where

$$y = \ln(Y/L),\ \ a = \ln A,\ k = \ln(K/L) \text{ and } f = F/L.$$

From (8) and (9) it follows that

$$\begin{aligned} \mathrm{El}_F Y &= f\frac{\partial y}{\partial f} = \beta_2\left(\lambda + f\right)^{-1} f \\ \mathrm{El}_L Y &= 1 - \beta_1 - \mathrm{El}_F Y \\ \mathrm{El}_K Y &= \beta_1. \end{aligned} \tag{10}$$

To study the case where λ is large, we reformulate (9) as

$$y = a^* + \beta_1 k + \beta_2^* \ln\left(1 + \frac{f}{\lambda}\right) \tag{11}$$

where

$$\beta_2^* = \beta_2/\lambda \text{ and } a^* = a + \beta_2 \ln\lambda. \tag{12}$$

Where λ is large,

$$\ln\left(1 + \frac{f}{\lambda}\right) \simeq f/\lambda. \tag{13}$$

Then we can reformulate (11) as

$$y = a^* + \beta_1 k + \beta_2^* f, \tag{14}$$

It follows that

$$\mathrm{El}_F Y = \beta_2^* f \tag{15}$$
$$\mathrm{El}_L Y = 1 - \beta_1 - \beta_2^* f.$$

Note that the parameter β_2^* in (14) has a different interpretation from β_2 in (9).

The limiting case of (14), i.e., when $s = \infty$, is particularly interesting because it allows an approximation when the depreciation rate of R&D capital, δ, is small, similar to Griffith et al. (2004). Then, as we show in Appendix A,

$$\Delta y_t \simeq \Delta a_t^* + \beta_1 \Delta k_t + \varrho \left(\frac{\widetilde{R}_{t-1}}{Y_{t-1}} \right) + \varrho(\alpha - 1) \left(\frac{\widetilde{N}_{t-1}}{Y_{t-1}} \right) - \eta \Delta \ln L_t, \tag{16}$$

where ϱ can be interpreted as the expected return to R&D: $\varrho \equiv E\left(\partial Y / \partial F\right)$ and η is the expected (mean) value of $\mathrm{El}_F Y$: $\eta \equiv E(\mathrm{El}_F Y)$.

4 Sample and variable construction

For our analysis, we have constructed a panel of annual firm-level data for Norwegian firms with at least three consecutive observations during 2001–2009. The base for the sample is the R&D statistics, which are survey data collected by Statistics Norway. These data comprise detailed information about firms' R&D activities, such as total R&D expenses (divided into internally performed R&D and externally purchased R&D), grants from the RCN, the number of employees engaged in R&D activities, and the number of man-hours worked in R&D. Each survey contains about 5000 firms. Only firms with more than 50 employees are automatically included in the survey. For smaller firms (with 5–49 employees) a stratified sampling scheme is employed. The stratification is based on industry classification (NACE codes) and firm size. However, these smaller firms are not representative of firms of their size and industry, because they have a higher probability of engaging in R&D. Hence, to reduce the problem of endogenous sample selection, we include only firms with more than 50 employees in our analysis. Currently, data are available for 1993, 1995, 1997, 1999, and *annually* from 2001 to 2009. The information from all available surveys is used for the construction of R&D capital stocks.

Table 1: Overview of variables and data sources

Variables	Definition	Data sources
Y	Output (net value added)	accounts statistics
$\widetilde{R}$	R&D investments	R&D statistics
$\widetilde{N}$	Grants from the RCN	R&D statistics
R	Total R&D capital stock	R&D statistics
N	RCN-financed R&D capital stock	R&D statistics
K	Total capital stock	accounts statistics
L	Man-hours	REE
h	Share of man-hours worked by high-skilled workers	REE, NED
Derived variables:		
y	Log of labor productivity: $\ln(Y/L)$	
k	Log of capital intensity: $\ln(K/L)$	
O	$R - N$	
F	$(\alpha N^{\rho} + O^{\rho})^{\frac{1}{\rho}}$	
f	F/L	

The data from the R&D statistics are supplemented with data from three different registers: The accounts statistics, the Register of Employers and Employees (REE), and the National Education Database (NED). Table 1 presents an overview of the main variables and data sources used in our study. The data sources are described in more detail in Appendix B.

Output, Y, is net value added at factor cost and computed as the sum of operating profits net of depreciation and labor costs and deflated by the consumer price index. R&D investment, $\widetilde{R}$, is yearly R&D investment and $\widetilde{N}$ are the grants from RCN as they are reported in the questionnaire, deflated by a price index for R&D investment based on the price indices from the national accounts for the various components making up total R&D. According to Hall et al. (2010) the choice of deflator for R&D expenditures usually does not matter much for the econometric results for the main parameters of interest.

The (real) R&D capital stock (R) at the beginning of a given year t is computed by the perpetual inventory method using (3) and a constant rate of depreciation $\delta = 0.15$ (for details, see Cappelen et al., 2012). Following Hall and Mairesse (1995), the benchmark for the R&D capital stock at the beginning of the observation period for a given firm, R_1, is calculated as if it were the result of an infinite R&D investment series, $\widetilde{R}_{-t}$, $t = 0, 1, 2, ...$, with a fixed presample growth rate $g = 0.05$ (cf. equation

(5) in Hall and Mairesse, 1995). A separate capital stock, N, is calculated in the same way, using $\widetilde{N}$ instead of $\widetilde{R}$ to accumulate the capital stock. Then $O = R - N$ is the R&D capital stock financed from *other* sources than RCN.

To construct the physical capital stock, K, we used information from the accounts statistics. The accounts statistics distinguish between several groups of physical assets. To obtain consistent definitions of asset categories over the whole sample period, all assets have been divided into only two types: equipment, denoted by e, which includes machinery, vehicles, tools, furniture and transport equipment, and buildings and land, denoted by b. The expected lifetimes of the physical assets in group e (of about 3–10 years) are considerably lower than those of the assets in group b (about 40–60 years). Total capital, K, is then an aggregate of equipment capital, e, and building capital, b. We use the book value as a measure of the capital stock. This is justified on the grounds of the short time series for each firm and corresponds to the approach taken by Power (1998) and Baily et al. (1992). When aggregating the two capital types, we use a Törnqvist volume index with time-varying weights that are common across firms in the same industry (see OECD, 2001).

Man-hours, L, is the sum of all individual man-hours worked by employees in the given firm according to the contract. For each firm, we distinguish between two educational groups, high- and low-skilled. High-skilled workers are those who have postsecondary education, i.e., persons who have studied for at least 13 years (for a description of the educational levels, see Table 6 in Appendix B). To construct h, man-hours worked by high-skilled persons are aggregated to the firm level and divided by the total number of man-hours worked in the firm.

As mentioned above, to avoid the problem of endogenous sample selection, only firms with more than 50 employees are included in our analysis. We further exclude from the sample firms with incomplete information or with extreme values for the variables of interest. We need to use the panel structure of the data in order to address the endogeneity problem that arises with respect to input choices and to be able to conduct a dynamic analysis. Hence, only firms with observations in at least three consecutive years are kept. The final sample contains about 1900 firms. Descriptive statistics for the main variables and firms in the final sample are presented in Appendix C.

5 Implementations and results

5.1 Estimation

In addition to the variables in Eq. (9), our analysis includes the share of man-hours worked by high-skilled workers, h_{it}, dummies for the firm's age, industry, and location, whether the firm cooperates with other firms in their R&D activities, and whether the firm uses an external research institute for their R&D. The dummy variables are collected in the vector D_i. Then

$$y_{it} = \beta_1 k_{it} + \beta_2 \ln(1 + f_{it}/\lambda) + \beta_3 h_{it} + \beta_4' D_i + \nu_i + \zeta_{it}, \tag{17}$$

where the indices $i = 1, ..., N$ and $t = 1, ..., T$ denote firm and time, respectively, ν_i represents a fixed firm-specific effect and ζ_{it} is an error term. We allow the error term, ζ_{it}, in (17) to follow a first-order autoregressive process, i.e.,

$$\zeta_{it} = \phi \zeta_{i,t-1} + \varepsilon_{it}, \tag{18}$$

where

$$|\phi| < 1,\ E[\varepsilon_{it}] = 0,\ E[\varepsilon_{it}^2] = \sigma_\varepsilon^2$$

and

$$Cov[\varepsilon_{it}, \varepsilon_{jt}] = 0 \text{ if } t \neq s \text{ or } i \neq j.$$

Multiplying (17) by ϕ and quasi-differencing, we get a dynamic panel data equation:

$$\begin{aligned} y_{it} = {} & \phi y_{i,t-1} + \beta_1 k_{it} + \varphi_1 k_{i,t-1} + \beta_2 \ln(1 + f_{it}/\lambda) + \varphi_2 \ln(\lambda + f_{i,t-1}) \\ & + \beta_3 h_{it} + \varphi_3 h_{i,t-1} + \varphi_4' D_i + \varpi_i + \varepsilon_{it}, \end{aligned} \tag{19}$$

where

$$\begin{aligned} & \varphi_1 = -\phi\beta_1,\ \varphi_2 = -\phi\beta_2, \varphi_3 = -\phi\beta_3, \\ & \varphi_4 = (1-\phi)\beta_4,\ \varpi_i = (1-\phi)\nu_i. \end{aligned} \tag{20}$$

Equation (19) is a first-order difference equation, which can be solved by repeated substitution of lagged values $y_{i,t-1}$, $y_{i,t-2}$, and so forth. If we do this, we will see that every value of y_{it} depends on ω_i and all $\varepsilon_{i,t-s}$ for $s \geq 0$. Thus, $y_{i,t-1}$ is correlated with the firm-specific effect, ω_i, but not with ε_{it}. Moreover, we assume that k_{it}, f_{it} and h_{it} are predetermined endogenous variables, i.e., determined at the beginning of t, and hence correlated with ω_i and $\varepsilon_{i,t-s}$ for $s > 0$.

Even if the nonlinear parameters (λ, ρ, α) were known, the estimation of equation (19) by means of least squares will give inconsistent estimators. The usual method for addressing the endogeneity problem is to estimate equation (19) in first-differenced form in order to exclude ω_i from the equation and then use instruments for the endogenous variables.

To estimate the model, we performed a grid search in the (λ, ρ, α)-space, where, for each value of (λ, ρ, α), we estimate the remaining parameters in (19) using the generalized method of moments (GMM) estimator proposed by Arellano and Bond (1991), which uses lagged levels and first differences of the endogenous variables as instruments. Their method is implemented in STATA as *xtabond*. Our iterative estimation procedure converges when the GMM-criterion function of Arellano and Bond is minimized [3]. Table 10 in Appendix C shows the value of the criterion function for a wide range of (s, λ)-values when $\alpha = 1$. It turned out that $\widehat{s} = \infty$ $(\widehat{\rho} = 1)$ and $\widehat{\lambda} > 140$ for all $\alpha \in [0, 2]$, and hence for all reasonable values of α. For all practical purposes we can therefore assume also that $\widehat{\lambda} = \infty$. Inserting $\rho = 1$ in (7), we can write

$$\begin{aligned} f &= F/L = \alpha N/L + O/L \\ &= R/L + (\alpha - 1)N/L. \end{aligned} \tag{21}$$

Moreover, because λ is large, it follows from (13) that $\ln(1 + f_{it}/\lambda)$ can be replaced by f_{it}/λ. Using (12) and (21) in (17), we then obtain

$$y_{it} = \beta_1 k_{it} + \beta_2^* \frac{R_t}{L_t} + \beta_2^*(\alpha - 1)\frac{N_t}{L_t} + \beta_3 h_{it} + \beta_4' D_i + \nu_i + \zeta_{it}. \tag{22}$$

The corresponding dynamic regression equation can be expressed as

$$\begin{aligned} y_{it} = \phi y_{i,t-1} + \beta_1 k_{it} + \varphi_1 k_{i,t-1} + \beta_2^* \frac{R_t}{L_t} + \beta_2^*(\alpha - 1)\frac{N_t}{L_t} + \\ \varphi_2^* \frac{R_{t-1}}{L_{t-1}} + \varphi_2^*(\alpha - 1)\frac{N_{t-1}}{L_{t-1}} + \beta_3 h_{it} + \varphi_3 h_{i,t-1} + \varphi_4' D_i + \varpi_i + \varepsilon_{it}, \end{aligned} \tag{23}$$

[3] This is asymptotically equivalent to maximizing the Wald statistic provided by STATA as a goodness-of-fit test of the model against an alternative with only a constant term.

where $\varphi_2^* = -\phi\beta_2^*$ and ε_{it} is white noise.

Note that the parameters β_1, β_2^* and β_3, can be interpreted both as short- and long-run coefficients under the restrictions (20). For example, from (23) the long-run effect on y_{it} of a *permanent* unit change in k_{it} equals $(\beta_1 + \varphi_1)/(1-\phi)$, which is equal to β_1 under the restrictions (20). Similarly, the long-run coefficient of R/L, is $(\beta_2^* + \varphi_2^*)/(1-\phi)$, which is equal to β_2^*. There are several possible estimators of the long-run coefficients. One is the estimated coefficient of k_{it} in (23), $\widehat{\beta}_1$. However, this estimator is not robust against specification errors in (20). A more robust estimator is the long-term coefficient of k_{it} derived from (23): $\widehat{\beta}_1^{LR} = (\widehat{\beta}_1 + \widehat{\varphi}_1)/(1-\widehat{\phi})$. If the model is correctly specified, $\widehat{\beta}_1$ should be close to $\widehat{\beta}_1^{LR}$. A third method is to impose (20) a priori when estimating (23). We will pursue the first and second approach here and test whether the restrictions (20) are valid or not.

The final estimates are presented in Table 2. As a benchmark we also present fixed-effects (FE) estimators of (22). The FE estimator is a conventional within-estimator applied to equation (22). However, this method yields biased estimates due to the endogeneity of explanatory variables, as described above.

Both the FE and GMM estimators of the coefficient of the aggregate R&D capital stock variable, R_t/L_t, are positive and significant. However, the estimated (long-run) coefficient is notably smaller using FE (0.10) than GMM (0.29). Note that the estimated short-run coefficient of R_t/L_t (0.23) is close to the long-run coefficient (0.29). This gives support to the parameter restrictions (20). The estimates of $\beta_2(\alpha-1)$ (the coefficient of N_t/L_t) are not significantly different from zero when using any of the methods. These results indicate that R&D capital subsidized by RCN adds no more or less to a firm's productivity than other R&D projects and that this is a robust finding.

As expected, we find a significant positive relation between capital intensity, k, and labor productivity: the estimated elasticity of tangible capital is around 0.1 using GMM. The FE estimate is much smaller. Seen together, these results indicate that the FE estimator of the coefficients of both the physical capital stock (k) and the R&D capital stock (R/L) are biased downwards. With regard to the variable h (share of man-hours by high skilled workers), the results are ambiguous. GMM

Table 2: GMM estimates of the productivity equation. Robust standard errors in brackets

Dependent variable: y_t	GMM-estimates				FE (Within)	
Explanatory variables,[a)]	short-run coeff.[b)]		long-run coeff.[c)]		estimates[d)]	
y_{t-1}	0.38	[0.03]***	–		–	
k_t	0.09	[0.02]***	0.10	[0.03]***	0.03	[0.00]***
k_{t-1}	−0.03	[0.02]*	–		–	
R_t/L_t	0.23	[0.03]***	0.29	[0.06]***	0.10	[0.04]**
R_{t-1}/L_{t-1}	−0.05	[0.03]*	–		–	
N_t/L_t	−0.59	[0.38]	−1.00	[1.44]	−0.60	[1.26]
N_{t-1}/L_{t-1}	−0.02	[0.77]	–		–	
h_t	−0.09	[0.16]	0.14	[0.24]	0.16	[0.08]**
h_{t-1}	0.18	[0.14]				
Number of observations		7124			10976	
Number of firms		1886			1886	
R^2					0.17	

Notes: *significant at 10 percent **significant at 5 percent ***significant at 1 percent

a) Dummies for firm age, region, industry, cooperation, and time are included in the analysis, but not reported here

b) Estimates of coefficients of dynamic equation (23): $\widehat{\phi}, \widehat{\beta}_k, \widehat{\varphi}_k$, etc.

c) Derived long-run coefficients from (23): $(\widehat{\beta}_k + \widehat{\varphi}_k)/(1-\widehat{\phi})$, etc.

d) Fixed-effects estimator of (22)

yields no significant coefficient estimates, whereas the FE estimator is positive, but significant only at the 10 percent level. The reason may be that both the FE and GMM estimator eliminate regressors that are constant over time, and poorly identify effects of variables that exhibit little within-firm variation, which is the case for h_{it}.

The estimate of ϕ in Table 2 – the coefficient of $y_{i,t-1}$ – is equal to 0.38 and is highly significant. Thus the error term in (19) exhibits strong serial correlation. Note that from (19) and (20) the coefficient, φ_2, of R_{t-1}/L_{t-1} should satisfy the constraint $\varphi_2 = -\phi\beta_2$. This constraint, and the other parameter restrictions in (20), are tested in Table 3. Neither of the restrictions is rejected by the statistical tests. As also seen from Table 3, the Arellano–Bond test of zero first-order autocorrelation in the error term ζ_{it} in (22) is rejected, but not for second-order autocorrelation. This confirms that ζ_{it} follows a first-order autoregressive process, as assumed in (18). We also applied a Sargan test to test the validity of the overidentifying restrictions with regard to the instrumental variables. With a χ^2-test statistic of 125.55 and 121 degrees of freedom, we cannot reject this hypothesis. All these specification tests, seen together, give strong support to our econometric specification.

Table 3: Test of parameter restrictions and significance of derived long-run coefficients

	Observed value (z) of test statistic (Z)	Level of significance $\Pr(Z > z)$
Test of parameter restrictions (20)*:		
$\varphi_1 = -\phi\beta_1$	0.32	0.75
$\varphi_2^* = -\phi\beta_2^*$	1.38	0.17
$\varphi_3 = -\phi\beta_3$	1.21	0.23
$(\alpha - 1)\varphi_2^* = -\phi\varphi_2^*(\alpha - 1)$	−0.32	0.75
Arellano–Bond test of zero autocorrelation in errors*		
order 1	−10.74	0.00
order 2	0.28	0.77
Sargan test of overidentifying restrictions**	125.55	0.10

Notes: *t-test **test statistics is distributed as $\chi^2(107)$

5.2 Return to R&D

GMM is the most appropriate method to handle the problem of endogeneity and autocorrelation in the residuals. From the GMM estimates in Table 2, we can calculate the elasticity of net value added with respect to R&D, $\mathrm{El}_F Y$, for any firm. Using (15),

$$\mathrm{El}_F Y = \beta_2^* \frac{F}{L},$$

whereas the marginal return to R&D capital, $\partial Y/\partial F$, equals

$$\frac{\partial Y}{\partial F} = \beta_2^* \frac{Y}{L}.$$

Using our long-run estimate of β_2^* $(= 0.29)$ and the mean value of F/L for firms with positive R&D $(= 0.116)$, we find that the estimated mean of $\mathrm{El}_F Y$ is 3.3 percent. The derived marginal returns have a mean value of 10.1 percent and median of 7.9 percent (see Table 4). Other percentiles are also depicted, e.g., the 10 percent and 90 percent percentiles are 5.1 and 15.3 percent, respectively. These figures are within the range of estimates obtained in the empirical literature.

To illustrate the robustness of these results, Table 4 shows the distribution of $\partial Y/\partial F$ when the model is estimated either on the full sample (superscript a) or the subsample of firms with positive R&D capital stock (superscript b), and also in the case when $\lambda = 0$ (i.e., a Cobb–Douglas production function). Both the mean value

Table 4: Distribution of marginal returns to R&D, $\partial Y/\partial F$, for different models

Model specification	Mean	Percentiles				
		10 %	25 %	50 %	75 %	90 %
Main model,$^{a)}$ with $\lambda = \infty$						
All firms	0.101	0.051	0.062	0.079	0.108	0.153
Only firms with $R > 0$	0.108	0.051	0.063	0.083	0.114	0.160
Main model,$^{b)}$ with $\lambda = \infty$						
Only firms with $R > 0$	0.123	0.059	0.072	0.095	0.130	0.183
Cobb–Douglas $^{b)}$ ($\lambda = 0$)						
Only firms with $R > 0$	0.574	0.152	0.683	2.415	10.912	41.582

Notes: $^{a)}$ Estimated on full sample of firms; $^{b)}$ Estimated on subsample of firms having $R > 0$

and the percentiles in the distribution of $\partial Y/\partial F$ are shown in each case. The main findings from Table 4 are that for our estimated (main) model (i.e., $\lambda = \infty$), the distribution of $\partial Y/\partial F$ is not sensitive to whether we exclude firms with zero $R\&D$ or not, which is a strength of our model specification. On the other hand, if we assume a Cobb–Douglas production function ($\lambda = 0$), the distribution of $\partial Y/\partial F$ changes dramatically. The estimated mean return now becomes 57.4 percent and the median return becomes 241 percent, which are implausible numbers.

An alternative approach to estimating the average return to R&D is provided by the model described in equation (16), which assumed a "small" depreciation rate δ, $s = \infty$ and $\alpha = 1$. Under the same assumptions regarding the error term ε_{it} and explanatory variables as above, we can rewrite (16) as

$$\Delta y_{it} = \beta_1 \Delta k_{it} - \eta \Delta \ln L_{it} + \varrho \left(\frac{\widetilde{R}_{i,t-1}}{Y_{i,t-1}} \right) + \varrho(\alpha - 1) \left(\frac{\widetilde{N}_{i,t-1}}{Y_{i,t-1}} \right) + \beta_3 \Delta h_{it} + \Delta \varepsilon_{it}, \quad (24)$$

where $\varrho \equiv E\left(\partial Y/\partial F\right)$ and $\eta \equiv E(\mathrm{El}_F Y)$ (cf. (16)).

The estimation results for (24) are presented in Table 5, together with an extended version of the model, which is similar to Griffith et al. (2004), i.e., when the productivity gap variable (A_f/A) is included as an explanatory variable as in (5). The dependent variable is the first-differenced log net value added per man-hour, Δy_t. In this model the assumed rate of depreciation of R&D capital is small so that R&D intensity is the relevant variable to include as discussed earlier. The advantage of this approach is that we do not need to assume any specific number for the depreciation rate (only that it is small), nor do we have to impute the initial R&D capital stock. Looking at the instrumental variable estimates in the first column of Table

5 we obtain an estimate of the real rate of return to R&D (ϱ) of about 6 percent, whereas the estimate for the extended model (second column) is 13.2 percent. This latter estimate is almost significant at the 1 percent level, and close to the mean return derived from the model of Table 2 (estimated to be 10 percent).

The coefficient of $-\Delta \ln(L_t)$ in Table 5 can be interpreted as the (expected) elasticity of Y with respect to R&D capital, F, and is estimated as 24.4 percent. This is much higher than the estimated mean of $\mathrm{El}_F Y$ implied by the GMM estimates in Table 2 (3.3 percent). On the other hand, the estimate of the elasticity of tangible capital is negative, although insignificant. The effect on productivity of an increase in the share of employees with high education, Δh_t, is also estimated to be negative. More importantly, we have included a variable capturing the productivity effect of having R&D finance from RCN, $\widetilde{N}/Y$. The estimated coefficient is insignificant, implying that firms that receive finance from the RCN have the same returns on their R&D as firms that do not receive any funding from the RCN. Thus, in this case also our results support the view that we can add both kinds of R&D investments into a common aggregate, $\widetilde{R} = \widetilde{N} + \widetilde{O}$, because the rate of return to R&D is independent of the source of finance.

The second column of Table 5 shows the result of estimating equation (24) when we include the productivity gap variable (A_f/A) as in (5). This variable enters with a significant positive coefficient, meaning that firms that are far behind the frontier are "catching up" to firms that are close to the frontier. However, contrary to Griffith et al.'s (2004) findings, the estimated coefficient of the "absorptive capacity" term, i.e., R&D intensity ($\widetilde{R}/\widetilde{Y}$) interacting with the productivity gap variable (A_f/A), is insignificant. Again, we do not reject that RCN-funded projects have the same productivity effects as R&D in general.

6 Conclusions

In this paper, we have analyzed the effects of R&D on firm performance with a particular focus on R&D spending partly financed by the Research Council of Norway (RCN), using a comprehensive panel of Norwegian firms over the period 2001-2009. We have based our study on econometric models of the relationship between labor

Table 5: GMM estimates of productivity growth equation. Standard errors are shown in brackets

Dependent variable: $\triangle y_t$	Instrumental variable estimates			
Explanatory variables$^{a)}$	Basic model (24)		Extended model as in (5)	
Δk_t	-0.006	[0.006]	-0.004	[0.006]
$-\Delta\ln(L_t)$	0.244	[0.029]***	0.214	[0.028]***
$\widetilde{R}_{t-1}/Y_{t-1}$	0.063	[0.029]	0.132	[0.052]**
$\widetilde{N}_{t-1}/Y_{t-1}$	-0.550	[0.554]	-1.092	[1.334]
$\ln(A_f/A)_{t-1}$	–		0.105	[0.008]***
$\widetilde{R}_{t-1}/Y_{t-1}\times\ln(A_f/A)_{t-1}$	–		-0.059	[0.039]
$\widetilde{N}_{t-1}/Y_{t-1}\times\ln(A_f/A)_{t-1}$	–		0.348	[1.044]
Δh_t	-0.380	[0.183]**	-0.339	[0.181]*
Number of observations	7124		7124	
Number of firms	1886		1886	
R^2	0.048		0.086	

Notes: *significant at 10 percent **significant at 5 percent ***significant at 1 percent
$^{a)}$Dummies for firm age, region, industry, cooperation, and time are included in the analysis, but not reported here.

productivity and R&D. A number of specific assumptions need to be made to estimate the effects of R&D on productivity. In particular one must address whether or not to calculate the stock of R&D capital, or simply use R&D investment as an explanatory variable. We have specified several versions of our model to study the robustness of our results. An important issue is how to treat firms with zero R&D spending (about 50 percent of the firms in our sample). The model suggested in this study allows firms to have positive output without having a positive R&D capital stock, which contrasts with the classical Cobb–Douglas production model. Thus we have avoided manipulation of the data that would have been required to incorporate firms with zero R&D spending. Moreover, we distinguish between different types of R&D according to funding source and allow different projects to be imperfect substitutes in terms of economic returns.

The estimates of our preferred model yield results that are generally in line with the existing literature. R&D spending stimulates productivity growth at the firm level even after controlling for a number of possible effects relating to industries, common shocks, etc. We find that RCN-funded R&D spending generally has the same effect on productivity as total R&D spending and conclude that the source of finance of R&D matters little for the effects of R&D on productivity. To the extent that subsidies and grants from RCN increase R&D in the business sector, the effect is captured by a common R&D capital stock variable that includes all R&D spending, regardless of the source of finance. Based on our preferred model we estimate the returns to R&D to be roughly 10 percent and this rate of return applies both to RCN-funded and firm-funded R&D.

We have also found that when using our preferred specification of the production function at the firm level, it matters little for the estimated rate of return to R&D whether or not we include firms with zero R&D spending in the estimation sample; including only firms with positive R&D just marginally increases the estimated rate of return to R&D. On the other hand, when using a standard Cobb–Douglas production function and limiting the sample only to firms with positive R&D spending, the estimated returns to R&D becomes implausibly high.

The main argument for government subsidizes to R&D is usually that R&D creates spill over effects so that firms do not get all the returns from its own investment in R&D. Our finding suggests that this cannot be the only reason for public subsidies to R&D, since projects financed by the RCN earn a standard private rate of return. Instead, financing constraints or capital market imperfections seem to be the main obstacles for R&D in Norway. However, it may be the case the RCN has a tendency to select projects based on their internal rate of return supplemented by a statement by the applicant relating to additionality (that the project will not be carried out without the subsidy). If this is the case there is a possibility that current RCN practice to some extent neglects projects with low private returns but high social returns. Thus RCN should review its criteria in selecting R&D projects so that private returns are not emphasized too much compared to social returns.

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Appendix A: Derivation of (16)

By differencing (14), we obtain

$$\Delta y_t = \Delta a_t^* + \beta_1 \Delta k_t + \beta_2^* \Delta f_t. \tag{25}$$

If δ is small and $s = \infty$, then $F_t = R_t + (\alpha - 1)N_t$ and $\Delta F_t / F_{t-1} \simeq \widetilde{R}_{t-1}/F_{t-1} + (\alpha - 1)\widetilde{N}_t / F_{t-1}$. Now

$$\Delta f_t \simeq \frac{L_{t-1}\Delta F_t - F_{t-1}\Delta L_t}{L_{t-1}^2} = \frac{\Delta F_t}{F_{t-1}} f_{t-1} - \frac{\Delta L_t}{L_{t-1}} f_{t-1} \simeq f_{t-1}(\widetilde{R}_{t-1}/F_{t-1} + (\alpha - 1)\widetilde{N}_t/F_{t-1} - \Delta \ln L). \tag{26}$$

Thus

$$\Delta y_t \simeq \Delta a_t^* + \beta_1 \Delta k_t + \beta_2^* f_{t-1} \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \beta_2^* f_{t-1} \Delta \ln L_t.$$

Defining $\eta = \mathrm{El}_F Y$ and $\varrho = \partial Y / \partial F$, then by definition $\eta = \varrho F / Y$, and from (15) $\eta = \beta_2^* f$. Finally, from (25) and (26),

$$\begin{aligned}
\Delta y_t &\simeq \Delta a_t^* + \beta_1 \Delta k_t + \eta \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \eta \Delta \ln L_t \\
&= \Delta a_t^* + \beta_1 \Delta k_t + \varrho \frac{F_{t-1}}{Y_{t-1}} \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \eta \Delta \ln L_t \\
&= \Delta a_t^* + \beta_1 \Delta k_t + \varrho \left(\frac{\widetilde{R}_{t-1}}{Y_{t-1}} \right) + \varrho(\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} - \eta \Delta \ln L_t.
\end{aligned}$$

Appendix B. Data sources

Accounts statistics: All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, in particular, the information about operating revenues, operating costs and result, labor costs, the book values of a firm's tangible fixed assets at the end of a year, their depreciation, and write-downs.

The structural statistics: The term "structural statistics" is a general name for statistics of different industrial activities, such as manufacturing, building and construction, wholesale and retail trade statistics, etc. They all have the same structure and include information about production, input factors, and investments at the firm level. These structural statistics are organized according to the NACE standard and are based on General Trading Statements, which are given in an appendix to the tax return. In addition to some variables, which are common to those in the accounts statistics, the structural statistics contain data about purchases of tangible fixed assets and operational leasing. These data were matched with the data from the accounts statistics. As the firm identification number here and further we use the number given to the firm under registration in the Register of Enterprises, one of the Brønnøysund registers, which has operated from 1995.

R&D statistics: R&D statistics are the survey data collected by Statistics Norway every second year up to 2001 and annually from then on. These data comprise detailed information about firms' R&D activities, in particular, about total R&D expenses with division into internally performed R&D and externally performed R&D services, the number of employees engaged in R&D activities and the number of man-years worked in R&D. In each wave, the sample is selected with a stratified method for firms with 10–50 employees, whereas firms with more than 50 employees are all included. Strata are based on industry and firm size. Each survey contains about 5000 firms, although many of them do not provide complete information.

Register of Employers and Employees (REE): The REE contains information obtained from employers. All employers are obliged to send information to the REE about each individual employee's contract start and end, working hours, overtime and occupation. An exception is made only if a person works less than four hours per week in a given firm and/or was employed for less than six days. In addition, this register contains identification numbers for the firm and the employee, hence, the data can easily be aggregated to the firm level.

National Education Database (NED): The NED gathers all individually based statistics on education from primary to tertiary education and has been provided by Statistics Norway since 1970. We use this data set to identify the length of education. For this purpose, we utilize the first digit of the NUS variable. This variable is constructed on the basis of the Norwegian Standard Classification of Education and is a six-digit number, the leading digit of which is the code for the educational level of the person. According to the Norwegian standard classification of education (NUS89), there are nine educational levels in addition to the major group for "unspecified length of education". Education levels are given in Table 6.

Table 6: Educational levels

Tripartition of levels	Level	Class level
	0	Under school age
Primary education	1	1st – 7th
	2	8th – 10th
Secondary education	3	11-12th
	4	12th – 13th
	5	14th – 17th
Postsecondary education	6	14th – 18th
	7	18th – 19th
	8	20th+
	9	Unspecified

Appendix C: Tables with descriptive statistics

Table 7: Descriptive statistics for the main variables used in the final sample

Variable	Obs	Mean	Std.	Min	Max
$Y^{a)}$	10976	234071	2518593	3953	1.48E+08
$\widetilde{R}^{a)}$	10976	6444	41758	0	1551539
$R^{a)}$	10976	38182	231021	0	6982151
$\widetilde{N}^{a)}$	10976	70	667	0	32311
$N^{a)}$	10976	371	2285	0	51769
$K^{a)}$	10976	47449	642380	1.5	2.88e+07
$L^{b)}$	10976	475042	1033602	42862	3.40E+07
$h^{c)}$	10976	0.262	0.218	0	0.937
y	10976	-1.233	0.509	-3.644	1.766
k	10976	-4.313	1.623	-11.566	2.198
f	10976	0.133	0.379	0	6.94
$\widetilde{R}/Y$	10976	0.045	0.146	0	0.937

Notes: $^{a)}$- in 1000 NOK; $^{b)}$- in man-hours; $^{c)}$- in shares

Table 8: Firms' description in the final sample, 1886 firms

Firm characteristics	Share of firms (in %)	$\widetilde{R}/Y$	R/L	N/L	h (in %)
All firms	100	0.049	0.079	0.0011	25.8
50–99 employees	41.6	0.066	0.108	0.0018	26.3
100–249 employees	36.9	0.037	0.071	0.0008	26.0
250+ employees	21.5	0.028	0.065	0.0005	26.2
age 0–2	13.8	0.057	0.088	0.0018	27.1
age 3–5	13.2	0.055	0.089	0.0013	28.4
age 6–9	13.4	0.049	0.087	0.0012	30.4
age 10–14	15.9	0.046	0.092	0.0013	27.4
age 15+	40.6	0.042	0.078	0.0009	23.9
Capital region	29.8	0.051	0.114	0.0014	37.1
East coast	15.8	0.045	0.077	0.0005	20.2
East innland	6.5	0.039	0.071	0.0014	16.0
South	17.4	0.051	0.090	0.0015	24.8
West	16.9	0.035	0.045	0.0006	20.9
Central Norway	7.2	0.047	0.078	0.0010	22.5
North	6.4	0.029	0.041	0.0010	21.2
Manufacturing	50.0	0.049	0.082	0.0009	18.8
Construction	6.9	0.003	0.005	0.0001	14.3
Retail trade	8.1	0.029	0.063	0.0001	27.0
Transport	14.1	0.009	0.029	0.0003	21.2
Services	10.8	0.126	0.225	0.0048	65.6
Other industries	10.0	0.041	0.094	0.0013	40.6

Note: Based on the first firm-year observations

Table 9: Description of main variables by time period

	2001–2003	2004–2006	2007–2009
Number of firms	1351	1652	1416
$\widetilde{R}/Y$	0.052	0.044	0.039
R/L	0.070	0.085	0.086
N/L	0.001	0.001	0.001
h	24.8 %	26.2 %	26.8 %
Share of firms (R&D_$av > 0$)	54.4 %	54.7 %	49.6 %
$\widetilde{R}/Y \mid$ R&D_$av > 0$	0.095	0.080	0.078
$R/L \mid$ R&D_$av > 0$	0.123	0.145	0.156
$N/L \mid$ R&D_$av > 0$	0.002	0.002	0.002
$h \mid$ R&D_$av > 0$	26.8 %	29.4 %	31.4 %
Share of firms (*all* R&D > 0)	37.2 %	38.9 %	36.0 %
$\widetilde{R}/Y \mid$ *all* R&D > 0	0.128	0.104	0.104
$R/L \mid$ *all* R&D > 0	0.166	0.192	0.204
$N/L \mid$ *all* R&D > 0	0.003	0.003	0.003
$h \mid$ *all* R&D > 0	28.6 %	31.4 %	32.7 %
Share of firms (RCN_$av > 0$)	7.8 %	5.9 %	6.4 %
$N/L \mid$ RCN_$av > 0$	0.008	0.011	0.014
Share of firms (*all* RCN > 0)	1.5 %	2.0 %	2.5 %
$N/L \mid$ *all* RCN > 0	0.027	0.023	0.023

Note: R&D_$av > 0$ when $\widetilde{R} > 0$ in at least one year in the given period,
all R&D > 0 when $\widetilde{R} > 0$ in all years in the given period (the same for RCN).

Table 10: Value of criterion function to be maximized in grid search over different (s, λ)-values when $\alpha = 1$

$s \backslash \lambda$	0.01	...	0.09	0.1	0.2	...	1	...	130	140	150
1.001	1061.19	...	1149.16	1150.19	1145.59	...	1129.76	...	1121.67	1121.66	1121.66
...	...	...	...	...	...	...	...	...	...	...	...
1.01	1056.74	...	1145.17	1146.60	1144.44	...	1130.74	...	1119.10	1118.98	1118.87
...	...	...	...	...	...	...	...	...	...	...	...
1.05	1047.34	...	1128.91	1130.69	1135.58	...	1138.58	...	1102.59	1102.09	1101.64
1.1	1050.79	...	1121.44	1121.83	1122.32	...	1116.78	...	1083.55	1083.52	1083.44
1.15	1050.27	...	1115.37	1114.27	1105.71	...	1066.65	...	1077.65	1078.18	1078.78
1.2	1042.46	...	1104.13	1103.25	1098.44	...	1057.50	...	1093.67	1095.16	1096.55
1.25	1032.06	...	1093.33	1093.39	1095.06	...	1054.19	...	1104.66	1105.82	1106.87
1.3	1022.13	...	1082.66	1083.44	1090.60	...	1052.29	...	1110.79	1111.64	1112.40
...	...	...	...	...	...	...	...	...	...	...	...
5	969.93	...	1008.55	1009.35	1038.12	...	1061.74	...	1330.03	1349.04	1348.84
...	...	...	...	...	...	...	...	...	...	...	...
90	968.21	...	1006.52	1007.18	1036.16	...	1063.40	...	1344.17	1350.53	1350.37
100	968.20	...	1006.51	1007.17	1036.15	...	1063.40	...	1344.23	1350.58	1350.39
$s = \infty$	968.14	...	1006.44	1007.09	1036.08	...	1063.46	...	1344.66	1350.60	1350.40

Essay 5:

The innovative input mix: Assessing the importance of R&D and ICT investments for firm performance in manufacturing and services

The innovative input mix: Assessing the importance of R&D and ICT investments for firm performance in manufacturing and services

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February, 2015

Abstract
Business innovation is an important driver of productivity growth. In this paper I assess the importance of R&D and ICT investment for firm performance in manufacturing and service industries. Explicitly, I use an extended version of the CDM model that treats ICT together with R&D as the main inputs into innovation and productivity, and test it on a large unbalanced panel data set based on the innovation survey for Norway. Four different types of innovation and the number of patent applications are used as innovative output measures. I find that ICT investment is strongly associated with all types of innovation in both sectors with the result being strongest for product innovation in manufacturing and for process innovation in service industries. The impact of ICT on patenting is positive only in manufacturing. Overall, ICT seems to be less important than R&D for innovation, but more important for productivity. These results support the proposition that ICT is an important driver of productivity growth. Given the high rate of ICT diffusion in Norway, my results contribute also to explaining the so-called “Norwegian productivity puzzle”, i.e., the feature that Norway is one of the most productive economies in the OECD despite having a relatively low R&D intensity.

Key words: Innovation, ICT, R&D, Productivity, CDM model, Manufacturing and Services

JEL classification: D24, L60, L80, O3

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1. Introduction

Business innovation is regarded as a potentially important driver of productivity growth, both at the firm and the national level. At the micro level, business innovation has the potential to increase consumer demand through improved product or service quality and simultaneously decrease production costs. At the macro level, strong business innovation increases multifactor productivity, thus increasing international competitiveness, economic growth and real per capital incomes.[1] It is therefore of great interest to businesses and policy-makers to identify the factors that stimulate innovation and to understand how these factors interact. R&D is an important factor behind innovations, but it is not the only one. Today, firms invest in a wide range of intangible assets, such as data, software, patents, new organisational processes and firm-specific skills. Together, these non-physical assets make up a firm's *knowledge-based capital*, KBC (see OECD, 2013). A lack of proper control for intangible assets and underinvestment in KBC are seen as the main candidates for explaining the poor productivity performance of European countries relative to the USA.[2] The need for Europe to move into the *knowledge-based economy* and support investment in KBC has been an important focus of government policy in European countries (see OECD, 2013).

Recently, more and more attention has been devoted to the role of Information and Communication Technology (ICT) as an enabler of innovation (see, for instance, Vincenzo, 2011). ICT is one of the most dynamic areas of investment, as well as a very pervasive technology.[3] The possible benefits of ICT use to a firm include among others increased input efficiency, general cost reductions and greater flexibility in the production process. This technology can also stimulate innovation activity in a firm, leading to higher product quality and the creation of new products or services. Its use has the potential to increase innovation by improving possibilities for communication and speeding up the diffusion of information through networks. For example, technologies that allow staff to effectively communicate and collaborate across wider geographic areas will encourage strategies for less centralised management, leading to organisational innovation. Previous analyses confirm that ICT plays an important role in firm performance, *e.g*. Brynjolfsson and Hitt (2000, 2003), OECD (2004), Gago and Rubalcaba (2007), Crespi *et al.* (2007) and van Leeuwen (2008). These studies evaluate the effects of ICT use and innovation on productivity. A few recent studies, i.e. Hall *et al.* (2013), Vincenzo (2011) and Polder *et al.* (2009), focus on the direct link between ICT and innovation.

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[1] See, for instance, Crépon *et al.* (1998), Griffith *et al.* (2006) and Parisi *et al.* (2006) for the studies at the micro level, and van Leeuwen and Klomp (2006) for the study at the macro level.
[2] See, for instance, van Ark *et al.* (2003), O'Sullivan (2006), Moncada-Paternò-Castello *et al.* (2009), Hall and Mairesse (2009) and Hall *et al.* (2013).
[3] ICT is often referred to as a modern general purpose technology, GPT (see Bresnahan and Trajtenberg, 1995, for a definition of GPT, and Castilione, 2012, for an investigation of GPT features of ICT).

One aim of the current study is to assess the effects of ICT as an enabler of innovation in Norwegian firms and to assess its relative importance for innovation and productivity compared to R&D. Do effects differ for different types of innovations? Four types of innovations are under investigation: a new (or improved) product, a new (or improved) production process, an organisational innovation and a new marketing method. I also use a count of patent applications as an alternative measure of innovative activity in firms.

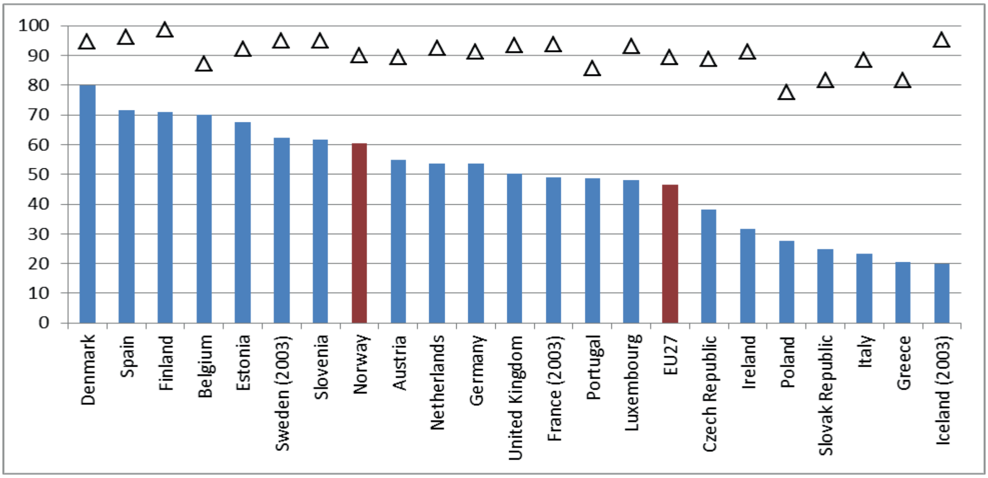

Figure 1 – Share of firms with access to broadband in 2004 (bars, 2003 when indicated) and in 2011 (Δ). Firms with 10 or more employees. *Source*: www.oecd.org, Key ICT Indicators

Another aim of the study is to investigate whether a high level of ICT diffusion in Norway could explain the so-called 'Norwegian puzzle', i.e. the fact that, while R&D spending in the Norwegian business sector as a share of GDP is below the OECD average, the productivity performance of Norwegian firms is among the strongest in the OECD (see OECD, 2007). Several studies endeavour to explain the 'Norwegian puzzle' (also referred to as the Norwegian productivity paradox). OECD (2008) points to the skill level of the adult population and financial support from the public sector as positive factors behind Norway's strong productivity performance. On the other hand, they find weak innovation activity in the manufacturing sector. Castellacci (2008) claims that the source of the Norwegian productivity paradox lies in the sectoral composition of the economy. Recently, Asheim (2012) discussed the lack of registration of all inputs and outputs in innovation activities and points to underreporting of R&D investments and innovation activities in the national R&D statistics. While providing several possible explanations for the 'Norwegian puzzle', none of these studies mention the high level of diffusion of ICT in Norway. For example, 60.3 per cent of Norwegian firms had access to broadband already in 2004, while the average for EU27 at that time was 46.5

per cent (see Figure 1). Also in 2011, when most European firms had access to broadband (the average for EU27 was 89.2 per cent), Norway was one of the leading European countries in e-commerce (see Figure 2 and OECD, 2011). [4] This fact is one of the reasons why the current paper directs the attention to data on Norwegian firms. What is the relative importance of ICT for productivity compared to other key inputs, such as R&D and human capital, in a country with a high rate of ICT diffusion? Are they complements or substitutes?

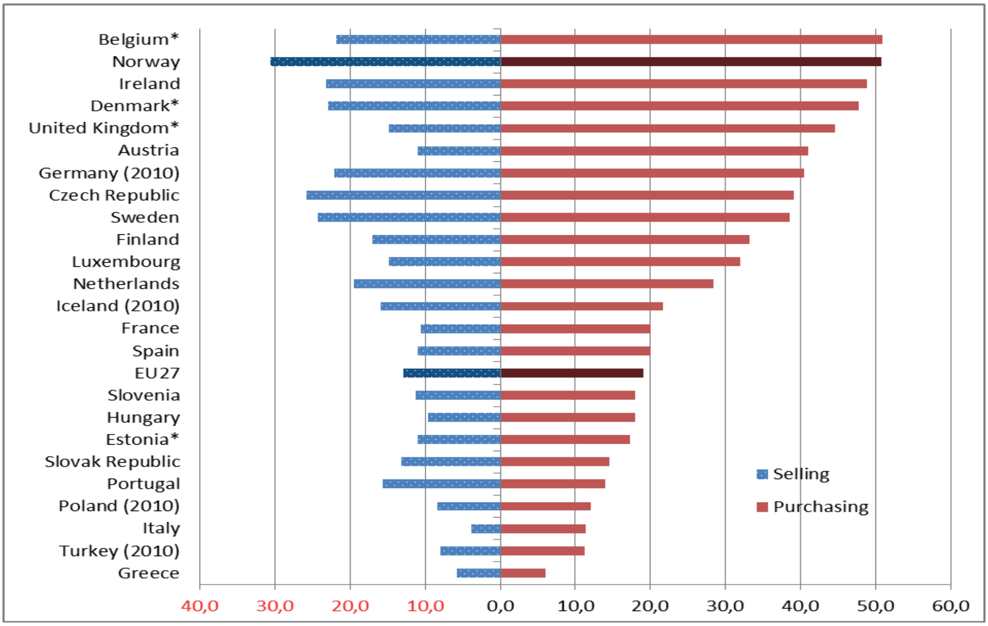

Figure 2 – Internet selling and purchasing in all industries in 2011 (2010 when indicated, * 2010 only for purchasing). Firms with 10 or more employees. *Source*: www.oecd.org, Key ICT Indicators

To investigate these research questions, I apply the currently most used model for analysing the link between innovation input, innovation output and productivity, the so-called CDM model (Crepon *et al.*, 1998). The standard version of the CDM model is a structural model that studies the following interrelated stages of the innovation chain: the choice by a firm of whether or not to engage in R&D; the amount of resources it decides to invest in R&D; the effects of these R&D investments on innovation output; and the impact of innovation output on the productivity of the firm. In the spirit of Polder *et al.* (2009) and Hall *et al.* (2013), I rely in this paper on an extended version of the CDM model, which treats ICT investment together

[4] Most countries explicitly use the OECD concept of Internet commerce, that is, goods or services that are ordered over the Internet but payment and/or delivery may be off line.

with R&D as two main inputs into innovation and productivity. While Hall *et al.* (2013) base their study on manufacturing firms alone, Polder *et al.* (2009) compare manufacturing firms with firms in services. Such comparison seems to be of substantial importance.

If we check the development of total factor productivity (TFP) in different industries in Norway in the three last decades compared to the USA,[5] we will see that most changes have taken place in the Wholesale and retail trade sector (see Figure 3).[6] While the productivity level in the manufacturing sector remained between 60 and 70 per cent below the corresponding productivity level in the USA during the period 1978–2007, the Wholesale and retail trade sector showed a great increase in relative TFP, and, by 2007, it had almost reached the US level. At the same time, the Wholesale and Retail trade industries (when studied at the more detailed industry level) are among the most ICT capital-intensive industries in Norway (see Table 3 in Rybalka, 2009), i.e. the average share of ICT capital services in total capital services in 2002–2006 was 26.8 per cent for the Wholesale and 17.4 per cent for the Retail trade (the corresponding share for manufacturing is just 5.7 per cent).[7] Hence, it is very important to account for industry heterogeneity when studying the effects of ICT. In order to account for such heterogeneity, I present results for manufacturing firms and firms in services separately (in addition to the analysis of the whole economy). Keeping in mind the explanations of the 'Norwegian puzzle' in previous studies, I also take into account the skill level of employees in Norwegian firms when analysing the effects of R&D and ICT on innovation and productivity.

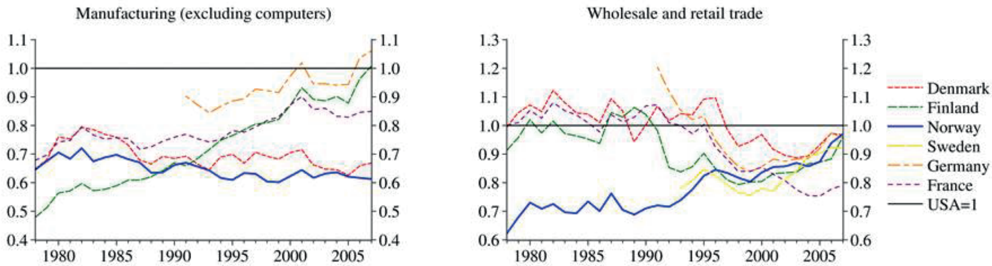

Figure 3 – TFP levels in Manufacturing and the Wholesale and retail trade from 1978–2007 in some European countries relative to the US industry equivalents. *Source*: von Brasch (2015) based on OECD and EU-KLEMS data

Beyond presenting results for the Norwegian economy, this paper contributes to the existing literature in several ways. Firstly, I take into account the *pervasiveness* of ICT and treat it in parallel with R&D as a

[5] Since US productivity has grown faster than productivity in Europe, the USA is often used as a reference country when studying productivity development in European countries, see, e.g., van Ark *et al.* (2003) and Aghion *et al.* (2009).
[6] All monetary measures for different countries are calculated in 1997 prices and USD using industry-specific Purchasing Power Parities from EU-KLEMS data (for details, see von Brasch, 2015).
[7] This measure of ICT capital services is constructed on the basis of information about firms' investments in hardware and software collected by Statistics Norway since 2002 (for details of the construction procedure, see Rybalka, 2009).

main input into innovation, rather than simply as an input into the production function. Secondly, in order to account for industry heterogeneity, I provide separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). Thirdly, I include marketing innovation in the analysis in addition to earlier investigated product, process and organisational innovation. All four types of innovation are equally represented in the data, which makes it possible to analyse the whole set of innovation types and enables a better understanding of the innovation process in the firm. Finally, I use the number of patent applications as an alternative measure for innovation. While the combination of different innovation types shows the *variety* of innovative processes in a firm, the number of patent applications reflects the *quality* of the innovation, i.e. only the best innovative products are expected to be protected by patent.

For the analysis, I use a rich firm-level data set based on the four recent waves of the *Community Innovation Survey* (CIS) for Norway (CIS2004, CIS2006, CIS2008 and CIS2010), which contains information on different firms' innovative activities. By supplementing these data with information on the number of patent applications from the Norwegian patent database and on ICT investment and other relevant information from different registers, I obtain an unbalanced panel of 14 533 observations of 8 554 firms. The estimation results indicate considerable differences between firms in manufacturing and service industries with respect to innovation and the productivity effects of R&D and ICT. While ICT investment is strongly associated with all types of innovation in both sectors, with the result being strongest for product innovation in manufacturing and for process innovation in service industries, the impact of ICT on patenting is only positive in manufacturing. The estimation results also confirm that R&D and ICT are both strongly associated with innovation and productivity, with R&D investment being more important for innovation, and ICT investment being more important for productivity. These results suggest that ICT is an important driver of productivity growth that, together with human capital, should be taken into account when trying to explain the 'Norwegian productivity puzzle'.

The paper is organised as follows. Section 2 summarises the main findings from previous studies and explains the extended version of the CDM model. Section 3 presents the data set, the main variables and some descriptive evidence. Section 4 presents the results, and Section 5 concludes.

2. Theoretical framework

2.1 ICT and firm performance

Several previous analyses confirm that ICT plays an important role in business success. One of the first attempts to quantify the role of ICT assets in firm performance in the form of productivity was made by Brynjolfsson and Hitt (1995). Since then, a broad range of empirical studies has emerged exploring the impacts of ICT on firm performance.[8] Most of these studies employ a production function framework to estimate the elasticity of output with respect to ICT capital, controlling for other factors, including innovations. However, very few of them focus on the direct link between ICT use and innovation.

As Koellinger (2005) puts it, 'ICT makes it possible to reduce transaction costs, improve business processes, facilitate coordination with suppliers, fragment processes along the value chain (both horizontally and vertically) and across different geographical locations, and increase diversification'. Each of these efficiency gains provides an opportunity for innovation. For example, technologies that allow staff to communicate effectively and collaborate across wider geographic areas will encourage strategies for less centralised management, leading to organisational innovation.

ICT also enables closer links between businesses, their suppliers, customers, competitors and collaborative partners, which are all potential creators of ideas for innovation (see Rogers, 2004). By enabling closer communication and collaboration, ICT helps businesses to be more responsive to innovation. For example, having broadband internet, a web presence and automated system linkages helps businesses to keep up with customer trends, monitor competitors' actions and get rapid user feedback, thereby helping them to exploit opportunities for all types of innovations.

Gretton *et al.* (2004) suggest the following two reasons why businesses' use of ICT encourages innovative activity. Firstly, ICT is a 'general purpose technology' that provides an 'indispensable platform' upon which further productivity-enhancing changes, such as product and process innovations, can be based. For example, a business that establishes a web presence sets the groundwork from which process innovations, such as electronic ordering and delivery, can be easily developed. In this way, adopting general purpose ICT makes it relatively easier and cheaper for businesses to develop innovations. Secondly, the spill-over effects from ICT use, such as network economies, can be sources of productivity gains. For example, staff of businesses that have adopted broadband internet are able to collaborate more closely with wider networks of academics and international researchers on the development of innovations.

A lack of proper control for intangible assets and the differences in industrial structure, specifically the smaller ICT producing sector, are seen as the main candidates for explaining the differences in productivity growth that are observed between Europe and the USA (for a comparative analysis of productivity growth in Europe and the USA, see, e.g., van Ark *et al.*, 2003; O'Sullivan, 2006; Moncada-Paternò-Castello *et al.*, 2009; and Hall and Mairesse, 2009). It is also true that firms' total R&D and ICT investments measured as shares of GDP are lower in Europe than in the United States and that the ICT gap is somewhat larger than that for R&D (see Figure 1 in Hall *et al.*, 2013). Hall *et al.* (2013) report so high rates

[8] See, for example, studies by Atrostic and Nguyen (2002), Biscourp *et al.* (2002), Bresnahan *et al.* (2002), Brynjolfsson and Hitt (2003), Crespi *et al.* (2007), Hall *et al.* (2013), Hempell (2005) and OECD (2004).

of return on both ICT and R&D investments for Italian firms that they suspect considerable underinvestment in both these activities.

Another line of literature investigates the importance of ICT for firms' organisation (see Brynjolfsson and Hitt, 2000, for a survey and Bloom *et al.*, 2009, for a recent study). Case studies show that the introduction of information technology is combined with a transformation of the firm, investment in intangible assets, and changes in relations with suppliers and customers. Electronic procurement, for instance, increases the control of inventories and decreases the costs of coordinating with suppliers, and ICT offers the possibility of flexible production: just-in-time inventory management, integration of sales with production planning etc.

The available microeconometric evidence shows that a combination of investment in ICT and changes in organisations and work practices facilitated by these technologies contributes to firms' productivity growth. For instance, Crespi *et al.* (2007) use Innovation survey data for the UK and find a positive effect on firm performance of the interaction between ICT and organisational innovation. Gago and Rubalcaba (2007) find that businesses that invest in ICT, particularly those that regard their investment as strategically important, are significantly more likely to engage in services innovation. Van Leeuwen (2008) shows that e-sales and broadband use significantly affect productivity through their effect on innovation output. However, broadband use only has a direct effect on productivity if R&D is not considered as an input to innovation. This approach is further developed by Polder *et al.* (2009). Their study finds that ICT investment is important for all types of innovation in services, while it plays a limited role in manufacturing, being only marginally significant for organisational innovation. Cerquera and Klein (2008), in contrast, find that more intense use of ICT brings about a reduction in R&D efforts in German firms. The results for nine OECD countries in Vincenzo (2011) are consistent with ICT having a positive impact on firm innovation activity, in particular on marketing innovation and on innovations in services. However, there is no evidence that ICT-intensive firms have greater capacity to introduce 'more innovative' (new-to-the-market) products, suggesting that ICT enables the adoption of innovation rather than the development of new products. For Italian manufacturing firms, Hall *et al.* (2013) find that ICT investment intensity is associated with product and organisational innovation, but not with process innovation, although not having any ICT investment is strongly negative for process innovation. These few recent papers, which investigate R&D and ICT investment jointly, have produced conflicting results as regards the impact of ICT on innovation. In addition, very few papers have investigated these effects separately for manufacturing and services. Hence, more evidence is needed.

2.2 Modelling framework

The currently most used model for analysing the link between innovation input, innovation output and productivity is called the CDM model (Crepon *et al.*, 1998). It was applied, for instance, in Lööf and Heshmati (2002), Parisi *et al.* (2006) and van Leeuwen and Klomp (2006). The standard version of the model contains three different blocks: (1) First, the firm decides whether or not to invest in R&D; and how much to invest, if it chooses to do so; (2) second, the innovative input leads to the innovative output (e.g. product or process innovation, new technology, organisational change); (3) finally, the innovative output leads to increased labour productivity. Several recent studies have modified the standard CDM model in order to include other factors than R&D in the knowledge production function. For example, Castellacci (2011) uses the CDM model to investigate the effects of industry-level competition on firms' innovation and productivity for Norway, while ICT is implemented in the CDM model by Griffith *et al.* (2006) for four European countries (France, Germany, Spain and the UK), Polder *et al.* (2009) for the Netherlands and by Hall *et al.* (2013) for Italy. These extensions of the standard model specification lead to extra difficulties in the estimation of the model, owing to the increased number of equations with qualitative dependent variables, for instance, when using different innovation types as a measure of innovative output. However, it is possible to bypass some of these difficulties by estimating the different blocks of the model sequentially.[9]

In this paper, I follow Polder *et al.* (2009) and Hall *et al.* (2013) and use an extension of the standard CDM model that analyses the effects of ICT on different stages of the innovative process. This version of the extended CDM model is presented in Figure 4. While Polder *et al.* (2009) use ICT as an additional input in the knowledge production function, but not in the production function, in Hall *et al.* (2013), the ICT investment is an input both in the production function and in the knowledge production function. While the former is in line with the more traditional view that ICT leads to productivity gains (e.g. through implementing new work practices and, hence, cost reductions and/or improved output); the latter introduces a less traditional view, i.e. that ICT may also stimulate innovation activity in the firm by speeding up the diffusion of information, promoting networking among firms, enabling closer links between businesses and customers, and leading to the creation of new goods and services. Consequently, this modelling framework treats ICT as a *pervasive* input rather than as an input in the production function only. In this paper, I apply the model extension used in Hall *et al.* (2013). A more detailed description of different blocks of the model follows below.

[9] Note that this estimation strategy requires bootstrapping of standard errors, which I provide for some of the models.

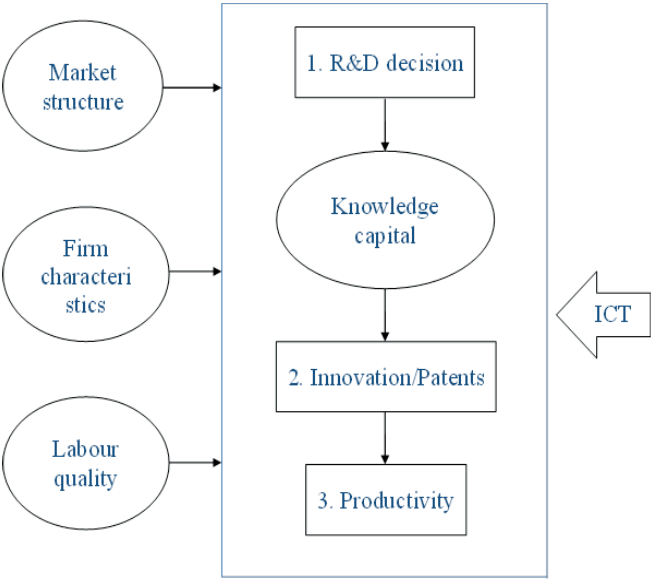

Figure 4 – CDM model augmented with ICT

Block 1: R&D input decision

This block does not differ from the first part of the standard CDM model. It models firm *i*'s decision to engage in R&D activities in period *t*. First the firm decides whether or not to start to invest in R&D in the given period; if it decides to invest, the firm then sets the amount of R&D investments. This statement of the problem can be modelled with a standard sample selection model (see Heckman, 1979):

$$rd_{it} = \begin{cases} 1 & \text{if } rd_{it}^{*} = x_{it}^{rd}\alpha_1 + e_{it} > c \\ 0 & \text{else} \end{cases}, \tag{1}$$

where rd_{it} is the observed binary endogenous variable equal to zero for non-R&D and one for R&D-performing firms, rd_{it}^{*} is a corresponding latent variable that expresses some decision criterion, such that a firm decides to invests in R&D if rd_{it}^{*} is above a certain threshold *c*, x_{it}^{rd} is a vector of firm characteristics (e.g. size, age, international orientation etc., and a constant term), α_1 is the associated coefficient vector, and e_{it} is an error term.

Once a firm has decided to engage in R&D activities, it must set the amount of resources devoted to R&D investments. Analogous to the previous equation and in line with the standard formulation of the CDM model, the latent R&D intensity of a firm i in a given period t, r_{it}^*, is represented as a function of another set of firm characteristics, x_{it}^r:

$$r_{it}^* = x_{it}^r \alpha_2 + \varepsilon_{it}\ , \tag{2}$$

where α_2 is the associated coefficient vector, and ε_{it} is an error term. The observed R&D intensity, r, is then equal to:

$$r_{it} = \begin{cases} r_{it}^* & \text{if } rd_{it} = 1 \\ 0 & \text{else} \end{cases}. \tag{3}$$

The pair of random disturbances e_{it} and ε_{it} is assumed to be jointly i.i.d. normally distributed, with zero mean and covariance matrix given by

$$\begin{pmatrix} 1 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix}, \tag{4}$$

where σ_e and σ_ε are the standard errors of e_{it} and ε_{it}, $\sigma_e = 1$ by standardisation, and ρ is their correlation coefficient. This model can be estimated by maximum likelihood.

Block 2: Innovation output

Let us now consider a model of how innovation occurs. R&D efforts lead to innovation output. Let $INNO^*$ be a latent variable that measures the extent of creativity/research activity within the firm. The higher the value of $INNO^*$, the higher is the probability that an innovation will occur. This modelling framework is influenced by Griliches (1990), Crepon *et al.* (1998) and Parisi *et al.* (2006). The main idea in this literature is that, by investing in R&D, the firm accumulates a knowledge capital stock, which plays an important role in its innovation activities. An extended version of the CDM model also includes an ICT intensity, *ict*, together with R&D intensity, *r*, in the knowledge production function:

$$INNO_{it}^* = \delta_1 \cdot r_{it} + \delta_2 \cdot ict_{it} + x_{it}^{inno} \beta + \eta_{it}\ , \tag{5}$$

where x_{it}^{inno} is a vector of different firm characteristics important for innovation output (e.g. firm size, industry, cooperation in R&D projects etc., and a constant term), δ_1, δ_2 and β are parameters (vectors) of interest, and η_{it} is an error term.

The previous empirical studies based on the CDM model use different innovation output measures to proxy unobserved knowledge, $INNO_{it}^{*}$, e.g. the share of innovative sales (applied, for example, in Crepon *et al.*, 1998, and Castellacci, 2011); different binary innovation indicators (applied, for example, in Griffith *et al.*, 2006, for product and process innovation; in Polder *et al.*, 2009, for product, process and organisational innovation; and in Hall *et al.*, 2013, for product, process and two types of organisational innovation); and patent applications counts (applied, for example, in Crepon *et al.*, 1998). In this paper, I estimate equations for the following measures of innovation output in the second model block: (i) the probability of any innovation; (ii) the probability of four different types of innovation (product, process, organisational and marketing innovation); and (iii) the expected number of patent applications. In the first case, an equation for the binary indicator of any innovation is estimated as a *probit* model. In the second case, a system of four equations for binary indicators of corresponding types of innovation is estimated as a *quadrivariate probit* model, accounting for the mutual dependence of the error terms. In the latter case, since numbers of patent applications are observed as integer numbers with many zero observations, they are modelled by *zero-inflated count data model* (see Chapter 18.4.8 in Greene, 2011, for a description of the model and Aghion *et al.*, 2009, for the application of the zero-inflated count data model to the patent data).[10] Note that the variables for R&D intensity, *r*, and ICT intensity, *ict*, are endogenous because these investments are simultaneously determined with innovation activities. I discuss this issue in more detail in under empirical model estimation in Section 4.

Block 3: Production function

The final block of the CDM model focuses on the effects of innovation output on labour productivity. In order to incorporate a firm's ICTs in the last block of the standard CDM model, I follow Hempell (2005) and use a traditional Cobb-Douglas production function with labour and two types of capital as inputs:

$$Y_{it} = A_{it} K_{it}^{\gamma_1} ICTK_{it}^{\gamma_2} L_{it}^{\gamma_3} . \tag{6}$$

In (6), Y_{it} is the output of firm *i* in period *t*, measured as value added in constant prices, K_{it} and $ICTK_{it}$ are the corresponding amounts of tangible and ICT capital inputs in constant prices, L_{it} is the labour input, and A_{it} is total factor productivity (TFP). The parameters γ_1, γ_2 and γ_3 correspond, respectively, to output elasticities of the two types of capital and labour, and TFP is assumed to be determined by:

[10] In this model, the zero outcomes can arise from one of two regimes, i.e. in one regime the outcome is always zero, and in the other, the usual count data generating process applies. Then, in the first step, the *inflation* equation that models the probability of falling in regime one is estimated by probit, and, in the second step, the standard count data generating process is estimated conditional on the outcome of the first step of estimation. I use a binary indicator for any type of innovation as a main *inflate* variable, since I expect that only innovative firms can apply for a patent. In addition, the inflation equation includes firm age, industry and location, and time dummies.

$$\ln(A_{it}) = \pi_0 + INNO_{it}\pi_1 + x^p_{it}\pi_2 + \zeta_{it}. \qquad (7)$$

In (7), $INNO_{it}$ is a vector of innovation output variables and x^p_{it} is a vector of different firm characteristics important for productivity (for instance, firm size, age and location); π_0, π_1 and π_2 are parameters (vectors) of interest and ζ_{it} is a white noise error term that comprises measurement errors and firm-specific productivity shocks. Dividing by L_{it} and taking logarithms on both sides of (6) yields:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 l_{it} + INNO_{it}\pi_1 + x^p_{it}\pi_2 + \zeta_{it}, \qquad (8)$$

where $\breve{\gamma}_3 = (\gamma_1 + \gamma_2 + \gamma_3 - 1)$ and the small letters *lp*, *l*, *k* and *ictk* denote the logarithm of labour productivity, *Y/L*, labour input, *L*, tangible capital intensity, *K/L*, and ICT capital intensity, *ICTK/L*, correspondingly.[11]

I also allow for heterogeneous labour input. Both economic theory and empirical evidence suggest that there is a key link between the skill level of the workforce and economic performance. Hence, omitting heterogeneity in the quality of labour may lead to overstating the productivity of ICT capital and innovation output. To account for this bias, I decompose a firm's workforce into employees who are high-skilled (with at least 13 years of education) and low-skilled (with less than 13 years of education).[12] Letting N_h and N_l denote the corresponding amounts of man-hours (where the total amount of man-hours $N = N_h + N_l$) and θ denote the productivity differential of high-skilled workers compared to low-skilled workers, effective labour input L_{it} is specified as:

$$L_{it} = N_{l,it} + (1+\theta)N_{h,it} = N_{it}(1+\theta h_{it}), \qquad (9)$$

where $h_{it} = N_{h,it} / N_{it}$ denotes the share of hours worked by high-skilled workers in the firm. Taking the logarithm of (9) and inserting the expression for l_{it} into (8) yields:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 n_{it} + \gamma_4 h_{it} + INNO_{it}\pi_1 + x^p_{it}\pi_2 + \zeta_{it}, \qquad (10)$$

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[11] Note that I do not impose constant return to scale, whereas ICT is allowed to affect productivity both directly (through the ICT capital variable) and indirectly (through the innovation output variable). The latter extension of the standard CDM model requires the use of exclusion restriction(s) or the non-linear functional form for identification of the total effect of ICT on productivity. I do use the non-linear functional form for identification of the model and I have some variables that are included in the vector of firm characteristics x^{inno}_{it} in the innovation equation and not in the vector x^p_{it} in the productivity equation. However, as I will discuss in more detail in Section 4, I cannot really claim to find causal effects of R&D and ICT on innovation and productivity. Therefore, all reported results in the paper should be viewed as representing associations rather than causal relationships.

[12] This number of years of education corresponds to completed upper secondary education or vocational training.

where the approximation follows from $\ln(1+\theta h_{it}) \approx \theta h_{it}$ and $\gamma_4 = \breve{\gamma}_3\theta$.[13] The inclusion of skill shares in the production function specification as in (10) in order to control for heterogeneity of labour quality is a common approach in the literature (see, for example, Lehr and Lichtenberg, 1999, Caroli and van Reenen, 1999, Bresnahan *et al.*, 2002, and Hempell, 2005). I use OLS for the estimation of this block of the model.

3. Variables construction and descriptive statistics

3.1 Data sources and variables

For the analysis, I use a rich firm-level panel data set based on the four recent waves of the *Community Innovation Survey* for Norway: CIS2004 (period: 2002–2004; $N = 4655$), CIS2006 (period: 2004–2006; $N = 6443$), CIS2008 (period: 2006–2008; $N = 6012$) and CIS2010 (period: 2008–2010; $N = 6595$). These data are collected by Statistics Norway as a part of the annual R&D survey (I refer to them as *R&D statistics*). They contain information on the inputs and outputs of firms' R&D and innovative activities, e.g. how much firms spent on R&D in the year of survey and whether firms have introduced different types of innovation over the three-year period prior to each survey. The firms included in the surveys are a large and representative sample of the Norwegian private sector. The firms with 10–50 employees are selected using a stratified sampling method based on industry classification (NACE codes) and firm size, whereas all firms with more than 50 employees are included. These data are then supplemented with information on the number of patent applications from the Norwegian patent database and ICT investments from Investment statistics for the years 2002–2010. Finally, by supplementing these data with information about firms and employees from different registers and excluding firms with incomplete information or with extreme observations for the key variables, I obtain an unbalanced panel of 14 533 observations on 8 554 firms.[14] Table 1 presents an overview of the main variables and the data sources applied in the study. A more detailed description of the data sources and distribution of the final sample across industries are provided in Appendix A.

[13] The first–order Taylor approximation is quite accurate if the values of θ and h are not too large. Anticipating some of the results and applying mean shares for h, the implicit product θh=0.05 is small enough for the approximation to work well (for values <0.1 the absolute error of the approximation is less than 0.005).

[14] In addition to requiring non-missing data for each variable except R&D intensity (since I use the predicted values for that variable) and firm age (a dummy for missing observations is used as one of the age dummies), I exclude the observations from the first and last percentiles of distributions for the following key variables: log R&D intensity, log ICT investment intensity, log ICT capital intensity, log tangible capital intensity and log value added per employee. The former has resulted in a reduction of the initial sample of 23 705 observations by about 31 per cent (N=2240 for missing observations on ICT investment and N=5147 for missing observations on other variables), while the latter reduced the initial sample by 5.7 per cent (N=1355). I also exclude the observations (N=430) for the firms in the 'Hotels and restaurants' industry (NACE 55), since they are only included in the CIS2010 data. Since I get few observational units with more than one year per firm (about 6o per cent of firms are only represented once in the sample and the average number of observations per firm is 1.6), I treat the final sample as cross-section data. However, in order to account for firm heterogeneity, I pool all available observations and adjust the standard errors for clustering at the firm level when estimating the model.

Four types of innovations are under investigation: a new (or improved) product for the firm, *pdt*, a new (or improved) production process, *pcs*, an organisational innovation, *org*, and a new marketing method, *mkt*. The definitions of these types of innovation comply with the Oslo Manual (OECD, 2005). For definitions and examples of different types of innovations, see Appendix B. In the Innovation survey, firms are asked to state whether they have introduced a given type of innovation during the last three years. The variable *inno* indicates whether the firm has introduced any type of innovation during the last three years. The corresponding dummy variables are measures of how innovative the firm is and are considered as dependent variables in the analysis of innovation output.

Table 1 – Overview of key variables and data sources

Variable	Definition	Data source(s)
pdt	Introduction of a new product (dummy)[a]	R&D statistics
pcs	Introduction of a new production process (dummy)[a]	R&D statistics
org	Introduction of an organisational innovation (dummy)[a]	R&D statistics
mkt	Introduction of a new marketing method (dummy)[a]	R&D statistics
inno	Introduction of any innovation (dummy)[a]	R&D statistics
sumpat	Number of patent applications[a]	Patent database
R	R&D investment[b]	R&D statistics
L	Number of employees	R&D statistics
ICT	ICT investment[b]	Investment statistics
ICTK	ICT capital services[b,c]	Investment statistics
K	Tangible capital services[b,c]	Accounts statistics
Y	Value added[b]	Accounts statistics
h	Share of man-hours worked by high-skilled employees[d]	REE/NED
Derived variables:		
r	R&D intensity: *R*/*L* (log)	
ict	ICT intensity: *ICT/L* (log)	
ictk	ICT capital intensity: *ICTK/L* (log)	
k	Tangible capital intensity: *K/L* (log)	
l	Number of employees (log)	
lp	Labour productivity: *Y/L* (log)	

[a] Measured over the three-year period preceding the year of the survey.
[b] The units of measurement are NOK thousands in real terms (base year = 2001).
[c] The variable is measured at the beginning of the year.
[d] Man-hours according to labour contracts.

Very few studies use patent applications as a proxy for innovation output (see the original version of the CDM model in Crepon *et al.* 1998, where they include such a variable). This is, probably, due to a lack of such information at the firm level. In this paper, I take advantage of having access to such data and use the number of applications for a patent, *sumpat*, as another measure of how innovative the firm is. This is simply the total number of patents applied for by the firm through the Norwegian Patent Office over the three years in the given sub-period. While the introduced innovation types show the *variety* of innovative process in the firm, the number of patent applications reflects the *quality* of the innovation, i.e. only the best innovative products are expected to be protected by patents.[15]

R&D investment, R, is annual R&D investment as it is reported in the questionnaire, deflated by the R&D deflator used in the national accounts (here and later, all monetary measures are calculated in 2001 prices).[16] R&D intensity, r, is the R&D investment per employee, R/L, where L is the number of employees.

Since 2002, Statistics Norway has collected micro-level information on investment expenditures on ICT, i.e. on purchased hardware and purchased and/or own-account software. ICT investment, *ICT*, is the total annual ICT expenditures. As deflators to obtain real expenditures I use the National Account price indices of the corresponding investment types. Then, by analogy to R&D intensity, r, ICT intensity, *ict*, is calculated as ICT investment per employee. These two variables are used as the main explanatory variables in the innovation output equation.

The ideal measure capturing the economic contribution of capital inputs in a production theory context is flow of capital services (see Draca *et al.*, 2007). Only in a very few studies the authors construct a measure of ICT capital based on information about investments in hardware and software (see, however, Hempell, 2005, and Farooqui and van Leeuwen, 2008). Using the Perpetual Inventory Method (PIM procedure) applied in these studies and using information on ICT flows over consecutive time periods, I construct a measure of ICT capital services, *ICTK*.[17] Further, the variable K is a measure of tangible capital services, which are calculated based on the book values of a firm's tangible assets (see, Rybalka, 2009, for details of the construction procedure for both capital measures). Then, ICT and tangible capital intensities, *ictk* and k, used in the production function analysis are calculated as the corresponding capital stock per employee at the *beginning* of year t. The final output, Y, is measured as value added in constant prices and defined as operating revenues minus operating expenses plus wage bills. This variable and K were deflated by the CPI.

Finally, the variable h is defined as the number of man-hours worked by employees with high education (corresponding to completed upper secondary education or vocational training) divided by the total number of man-hours in the firm. I assume that labour heterogeneity can also influence the innovation activity in the firm and control for it not only in the production function, but also in the innovation output equation.

In addition to the main variables described above, I use the following firm characteristics in the analysis:

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[15] For example, only 17 per cent of innovative firms in CIS2004 applied for a patent during 2002–2004.
[16] More than 60 percent of total R&D expenditures are labour costs.
[17] I use all available data on the firm's ICT investments from annual 2002–2010 Investment statistics for ICT capital construction.

- *Market location*: a set of dummy variables indicating whether a firm sells its *main* products or services in local/regional, national, European or other international markets. This variable indicates the location of firm's main competitors. The former category (local/regional market location) is the reference category.
- *Part of a group*: a dummy variable indicating whether a firm belongs to a group.
- *Received subsidy*: a dummy variable indicating whether a firm has received a subsidy for carrying out R&D during the three years of the survey.
- *Hampering factors* (*H*): a set of categorical variables indicating whether a firm considers the following factors as important obstacles to its innovative activities: 'high costs', 'lack of qualified personnel', and 'lack of information'. These variables take values from 0 ('no importance') to 3 ('highly important').
- *Positive R&D history*: a dummy variable indicating whether a firm has carried out any R&D during the three years preceding the observation year.
- *Cooperation on innovation*: a set of dummy variables indicating whether the firm cooperated with others (another firm or university/college/research institute) in Norway, Scandinavia, the EU or the rest of the world (or cooperation in general), when carrying out R&D during the three years of the survey.
- *Purchased R&D*: a dummy variable indicating whether a firm has purchased R&D from external providers.
- *Firm age*: a set of dummy variables indicating the firm age, i.e. 0-2, 3-5, 6-9, 10-15 or 16 years old and older. The latter category (mature firms) is the reference category.
- *Firm industry*: a set of dummy variables indicating the firm industry at the two-digit NACE level (see Table A1 for the distribution across industries of the final sample). [18] Manufacture of food products and beverages (NACE 15) is the reference industry for manufacturing firms and Wholesale (NACE 51) is the reference industry for firms in services and for the whole sample.
- *Firm location*: a set of dummy variables indicating the region where the firm is located, i.e. North, South, West, East coast, East inland, central Norway, and the capital region (Oslo and Akershus). The latter category is the reference category.
- *Year*: a set of time dummies indicating the year of the Innovation survey; 2004 is the reference year.

3.2 Descriptive statistics

Table 2 presents the mean values of the main variables for different data samples (more descriptive statistics for the final sample are reported in Table A2). Column (1) in Table 2 describes the final sample of 14 533 observations of 8 554 firms. In this sample, almost half of the observations (approximately 48 per cent)

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[18] At all estimation stages and for all sub-samples I include 2-digit industry dummies in order to control for industry specific differences. While differences may also be present within 2-digit industries, further specification is not possible due to the small number of observations in some of the sub-industries.

concern firms that engage in some sort of innovation activity, while only 30 per cent report positive R&D investment, with an average of NOK 108 000 per employee. This fact confirms that many firms may have some kind of innovative effort without reporting R&D (see Griffith *et al.*, 2006). While nearly 90 per cent of the firms in the sample invest in ICT, the intensity with which they invest is much lower compared to R&D investment intensity, i.e. less than NOK 24 000 per employee. Roughly 30 per cent of the employees are high-skilled workers on average.

Table 2 – Mean values of key variables for different samples (pooled CIS2004, CIS2006, CIS2008 and CIS2010)

	(1)	(2)	(3)	(4)	(5)
Sample:	Full sample (N=14533)	Obs. on innovative firms (N=6967)	Obs. on non-innovative firms (N=7566)	Obs. on manufacturing firms (N=6199)	Obs. on firms in services (N=6145)
Value added (VA) per employee[a,b]	610.0	640.0	582.4	561.4	685.3
Number of employees[b]	92.6	121.0	66.5	91.3	93.0
Firm age[b]	17.5	17.5	17.5	19.5	16.2
ICT capital services per VA[b]	0.034	0.040	0.029	0.021	0.053
Tangible capital services per VA[b]	0.060	0.062	0.059	0.074	0.049
Share of high-skilled[b]	29.0%	35.0%	23.4%	19.7%	43.8%
Part of a group[c]	61.7%	66.5%	57.3%	63.6%	62.0%
Market location: local/regional[c]	51.6%	38.7%	63.5%	42.6%	49.7%
Market location: national[c]	33.1%	39.6%	27.1%	36.5%	36.7%
Market location: European[c]	9.1%	12.7%	5.7%	12.7%	7.5%
Market location: world[c]	6.2%	9.0%	3.7%	8.2%	6.1%
Recipients of subsidies[c]	15.9%	30.3%	2.7%	21.3%	15.0%
Cooperation on innovation[c]	17.0%	32.0%	3.1%	22.4%	15.5%
Purchased R&D[c]	13.3%	25.1%	2.5%	19.6%	9.9%
R&D investors ($R>0$)[c]	30.1%	55.2%	7.0%	38.9%	29.0%
ICT investors ($ICT>0$)[c]	89.3%	92.8%	86.1%	88.9%	90.3%
R&D investment intensity[a,b,d]	108.0	112.7	73.6	68.2	165.8
ICT investment intensity[a,b,d]	23.6	26.7	20.5	14.8	36.3
Firms with at least one innovation[c]	47.9%	100%	-	55.0%	48.8%
Firms with product innovation[c]	28.8%	60.1%	-	35.8%	29.7%
Firms with process innovation[c]	21.5%	44.8%	-	25.6%	21.6%
Firms with organisational innovation[c]	21.6%	45.1%	-	23.7%	21.6%
Firms with marketing innovation[c]	25.8%	53.8%	-	29.8%	27.3%
Firms with at least one patent[c]	10.1%	18.4%	2.4%	14.5%	8.2%
Number of patent applications[b,e]	2.1	2.2	1.2	2.3	1.8

[a] Units are NOK thousands in real terms (base year = 2001) per employee.
[b] Mean values.
[c] Share of observations with corresponding firm characteristic.
[d] Calculated for the sample of firms with positive investment.
[e] Calculated for the sample of firms with at least one patent application.

Relatively few Norwegian firms have an international orientation, i.e. only 15 per cent of the firms sell their main products or services on the international market (Europe and rest of the world), while more than half of the firms (about 52 per cent) sell their main products or services on the local or regional market, and about 33 per cent operate at the national level. More than 60 per cent of the observations concern firms that belong to a group. The same high shares are observed by Castellacci (2011) for Norwegian CIS data and by Polder *et al.* (2009) for Dutch CIS data (compared to just 25 per cent of Italian manufacturing firms in Hall *et al.*, 2013). That could be the result of the over-representation of medium-sized and large firms in Norwegian CIS data (these firms are often part of a group), i.e. firm size distribution is skewed to the right, with an average of 92, but with a median of only 30 employees (see Table A2). Approximately 17 per cent have cooperated on innovation, either with a university/college/research institute or with another firm, while approximately 13 per cent of the firms purchased R&D services from an external provider. Only 16 per cent of firms in my final sample are R&D subsidy recipients, in contrast to Hall *et al.* (2013), where 42 per cent of the firms receive subsidies (however, their subsidy variable comprises subsidies both for R&D and for other types of investments).

Turning to the innovation output variables, all four types of innovation are well-represented in the data, the shares of observations varying between 21 and 29 per cent (see column 1 in Table 2). As for the combinations of different types of innovation, product innovation only (combination [1,0,0,0]), followed by all types of innovation (combination [1,1,1,1]), marketing innovation only (combination [0,0,0,1]) and organisational innovation only (combination [0,0,1,0]) are the most common innovation combinations among the innovative firms (see the observed frequencies for 16 combinations of four innovation types in Table C5). Not surprisingly, the distribution of the number of patent applications is extremely skewed to the right, with 90 per cent of observations being equal to zero and 80 per cent of those that applied for a patent being equal to one patent application (see Figure 5). Such a distribution of the number of patent applications can be captured by the zero-inflated count data models (see, e.g., Chapter 18 in Greene, 2011). This class of models takes into account that zero counts can arise from one of two regimes, i.e. in one regime, the outcome is always zero (in my case, if a firm does not innovate), and, in the other, the usual count data generating process applies (some innovative firms apply for a patent and some do not).

Columns (2) and (3) in Table 2 present a comparison of the main firm characteristics of innovative and non-innovative firms (the former are defined as those that have introduced at least one type of innovation in the survey period). The comparison shows a remarkable difference between the two groups, which is in line with the previous CDM analyses based on firm-level data for other countries (see, for example, Crepon *et al.*, 1998; and Hall and Mairesse, 2006). On average, innovative firms are much bigger in size, have a higher share of high-skilled employees, an international orientation and a higher probability of belonging to a group than non-innovative firms. They are also more capital intensive. However, the former group is only slightly more productive. About 55 per cent of innovative firms and only 7 per cent of non-innovative firms are R&D performing firms, which supports the fact that R&D is an important input for innovation output. While approximately 18 per cent of innovative firms have applied for at least one patent, 2 per cent of non-innovative firms also have at least one patent application in the patent database. The latter observation is possible if some of the non-innovative firms have applied for a patent for an innovation introduced during the previous three-year period.[19]

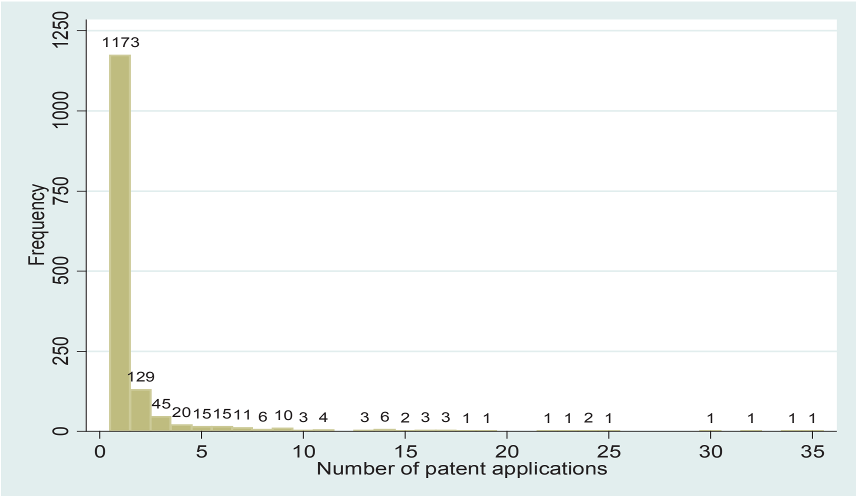

Figure 5 – Distribution of number of patent applications (with N=13066 for zero patent applications and N=8 for more than 35 patent applications).

Finally, columns (4) and (5) in Table 2 present a comparison of the main firm characteristics of manufacturing firms (NACE 15-36 in SN2002) and firms in service industries (NACE 51-74 in SN2002). We can observe a remarkable difference between these two groups. Being on average almost of the same size and slightly younger, firms in service industries are more productive, have a higher share of high-skilled man-hours and are much more ICT capital-intensive (although much less tangible capital intensive). Given that Business-related services (NACE 72-74) and Wholesale (NACE 51) were the most ICT capital-intensive industries in Norway in 2002–2006 (see Table 3 in Rybalka, 2009) and that these industries account for about 75 per cent of observations for the firms in service industries in the final sample (see Table A1), the latter observation is not surprising. At the same time, the firms in the service industries represented are less likely to have their main market abroad, and they also cooperate less on innovative activities, purchase R&D from external providers less often, and receive R&D funding less often. Not surprisingly, their innovative output is lower on average, both when proxied by different innovation types and by the number of patent applications. Interestingly, while there are fewer R&D investors among firms in service industries, those that do invest in R&D invest on average more intensively than R&D investors in manufacturing. One can also observe that the

[19] These numbers support my intuitive choice of a binary indicator for any type of innovation as a main *inflate* variable when estimating the probability of outcome (the number of patent applications) to be zero or nonzero, i.e. the innovators have much higher probability to apply for a patent than non-innovators.

rate of ICT diffusion is high in both sectors (the shares of ICT investing firms are 88.9 and 90.3 per cent, respectively). However, firms in service industries invest more intensively in ICT. Thus, compared to manufacturing firms, firms in service industries appear to be younger, more domestically oriented, and rely relatively more on ICT and skilled labour. Although less innovative, they are, however, more productive.

4. Econometric model specification and estimation issues

This section presents the econometric model specification for the extended version of CDM model presented in Section 2.

Econometric specification of block 1: R&D input decision

This block is the same for all model specifications. It models an R&D input decision by firm *i* in time *t* and contains two R&D equations corresponding to the theoretical model (1)–(4):

$$rd_{it}^{*} = x_{it}^{rd}\alpha_1 + e_{it}\,, \qquad (1')$$
$$r_{it}^{*} = x_{it}^{r}\alpha_2 + \varepsilon_{it}\,. \qquad (2')$$

Econometric specification of block 2: Innovation output

I use two proxies for innovation output when estimating the second model block based on equation (5), i.e., the probability of innovating and the number of patent applications. The probability of innovating can be estimated for any innovation (basic model) and for each of four different types of innovation (product, process, organisational and marketing innovation). The innovation equation when innovation output is proxied by *any type* of innovation is:

$$inno_{it}^{*} = \delta_1^0 \cdot r_{it}^{*} + \delta_2^0 \cdot ict_{it} + \delta_3^0 \cdot h_{it} + x_{it}^{inno}\beta^0 + \eta_{it}^0\,. \qquad (3a')$$

The system of equations for the probability of the *different types* of innovation is:

$$\begin{cases} pdt_{it}^{*} = \delta_1^1 \cdot r_{it}^{*} + \delta_2^1 \cdot ict_{it} + \delta_3^1 \cdot h_{it} + x_{it}^{inno}\beta^1 + \eta_{it}^1 \\ pcs_{it}^{*} = \delta_1^2 \cdot r_{it}^{*} + \delta_2^2 \cdot ict_{it} + \delta_3^2 \cdot h_{it} + x_{it}^{inno}\beta^2 + \eta_{it}^2 \\ org_{it}^{*} = \delta_1^3 \cdot r_{it}^{*} + \delta_2^3 \cdot ict_{it} + \delta_3^3 \cdot h_{it} + x_{it}^{inno}\beta^3 + \eta_{it}^3 \\ mkt_{it}^{*} = \delta_1^4 \cdot r_{it}^{*} + \delta_2^4 \cdot ict_{it} + \delta_3^4 \cdot h_{it} + x_{it}^{inno}\beta^4 + \eta_{it}^4 \end{cases}. \qquad (3b')$$

I model the probability of applying for a patent as a function of the binary indicator for any type of innovation, as well as firm age, industry and location, and time dummies. The patent equation is then specified as an expected number of patent counts for the firms that have positive probability of applying for a patent, $sumpat_{it}^{*}$, conditional on R&D intensity, *r*, ICT intensity, *ict*, and other variables equal to:

$$E(sumpat_{it} \mid r_{it}^{*}, ict_{it}, h_{it}, FSI_{it}, \eta_{it}^{5}) = \exp(\delta_1^5 \cdot r_{it}^{*} + \delta_2^5 \cdot ict_{it} + \delta_3^5 \cdot h_{it} + x_{it}^{inno} \beta^5 + \eta_{it}^5). \quad (3c')$$

Econometric specification of block 3: Productivity

The econometric specification of the productivity equation based on the theoretical model (6)–(10) is:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 L_{it} + \gamma_4 h_{it} + INNO_{it}^{*} \pi_1 + x_{it}^{p} \pi_2 + \zeta_{it}, \quad (4')$$

where $INNO^{*}$ is either the predicted probability of any innovation; or the set of dummies for the different combinations of innovation types: [1,1,1,1], [1,1,1,0], [1,1,0,1], etc. (with combination [0,0,0,0] as the reference category); or the expected number of patent applications per employee.[20]

This empirical model is a recursive nonlinear system of equations, each of which focuses on one of the steps in the innovation process. The first equation models the probability that a firm with characteristics x_{it}^{rd} engages in R&D activities. It is estimated for the whole sample of firms. The second equation focuses only on firms with positive R&D investment, $R > 0$, and studies how the R&D intensity of the firm, r_{it}^{*}, is affected by a set of firm characteristics x_{it}^{r}. The third equation analyses the link between two main innovation inputs (R&D and ICT), on the one hand, and innovation output (either any innovation, four different types of innovation, or the number of patent applications), on the other.[21] Finally, the fourth equation estimates the effects of innovation output together with ICT capital on the labour productivity of the firm (lp_{it}). When estimating the second and third model blocks, I also explore the influence of skill composition on the firm (h_{it}), together with firm characteristics x_{it}^{inno} and x_{it}^{p}, correspondingly. Table 3 describes different firm characteristics that are comprised in the vectors $x_{it}^{rd}, x_{it}^{r}, x_{it}^{inno}$ and x_{it}^{p} (marked by *x*) and other explanatory variables used in the estimation of equations (1′)–(4′).

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[20] Note that, to simplify the interpretation of the results, I use the predicted values for the number of patent applications divided by the number of employees in the firm as an explanatory variable in the productivity equation (such as *k* and *ictk*, which are the conventional and ICT capital per employee).

[21] The innovation equation (3a′) is estimated as a probit model. Equation (3b′) is a system of four equations with binary indicators of corresponding types of innovations. It is estimated as a quadrivariate probit model using the GHK (Geweke-Hajivassiliou-Keane) simulation algorithm (see Chapter 15 in Greene, 2011; and Cappellari and Jenkins, 2003), assuming the mutual dependence of the error terms. Finally, equation (3c′) is estimated as a zero-inflated negative binomial count data model by pseudo maximum likelihood.

Table 3 – Variables and methods used in the estimation of different model equations

	Eq. (1´)	Eq. (2´)	Eq. (3´)	Eq. (4´)
Dependent variable:	Dummy for R>0	Log(R&D spending per employee)	Any innovation/ four types of innovation / number of patent appl.	Log(VA per employee)
Explanatory variables:				
Log employment	*x*	*x*	*x*	*x*
Log employment squared	*x*	*x*	*x*	*x*
Positive R&D history[a]	*x*			
Market location[b]	*x*	*x*		
Part of a group[b]	*x*	*x*		
Hampering factors[b]	*x*	*x*		
Received subsidy[b]		*x*		
Cooperation in innovation[c]		*x*	*x*	
Purchased R&D[c]			*x*	
Log(R&D intensity)[d]			*r**	
Share of high skilled			*h*	*h*
Log(ICT intensity)[e]			*ict*	*ictk*
Log(tangible capital intensity)[e]				*k*
Innovation output[d]				*INNO**
Age dummies	*x*	*x*	*x*	*x*
Industry dummies	*x*	*x*	*x*	*x*
Regional dummies	*x*	*x*	*x*	*x*
Time dummies	yes	yes	yes	yes
Estimation method:	Maximum likelihood (ML) by Heckman procedure		Probit / Quadrivariate probit by GKH simulation / pseudo ML for zero inflated count data	OLS

Different firm characteristics that are comprised in the vectors $x_{it}^{rd}, x_{it}^{r}, x_{it}^{inno}$ and x_{it}^{p} are marked by *x*.

[a] Exclusion restriction when estimating (1´) and (2´) by Heckman procedure.
[b] Used to instrument the R&D intensity variable, *r**, when estimating (2´) and using predictions for *r** in (3´).
[c] Used to instrument the innovation output variable, *INNO**, when estimating (3´) and using predictions for *INNO** in (4´).
[d] Predicted from the previous estimation stage.
[e] Set to zero when corresponding investment is zero and dummies for such observations are included.

The choice of explanatory variables, such as *Market location*, *Part of a group*, *Received subsidy* and *Cooperation on innovation* is inspired by both Hall *et al.* (2013) and Polder *et al.* (2009). However, I also include the *Cooperation on innovation* (at the national, Scandinavian, European or world level) and *Purchased R&D* variables in the Innovation output equation. This choice is based on the results in Cappelen *et al.* (2012), who show that firms collaborating with others on their R&D efforts are more likely to be successful in their innovation activities and patenting.[22] Following Castellacci (2011), who estimates the

[22] At the same time, Cappelen *et al*. (2012) demonstrate that getting an R&D tax credit has a marginal effect on innovation (they only find a positive and significant effect for process innovation) and no effect on patenting. Hence, I choose not to control for receiving an R&D subsidy in the innovation equation (in line with Hall *et al.*, 2013, and Polder *et al.*, 2009).

CDM model based on Norwegian data, I also include *Hampering factors* (high costs, lack of qualified personnel and lack of information) in the estimation of the R&D choice model block. As Castellacci (2011) demonstrates, these factors are highly relevant for shaping the innovative process and are also valid instruments for handling the endogeneity problem of the R&D intensity variable when using it in the innovation output equation. While Hall *et al.* (2013) only control for the skill composition of the firm in the innovation output equation, I follow the standard CDM model in Crepon *et al*. (1998) and control for the skill composition of the workforce (share of high-skilled man-hours) also in the productivity equation. Further, I provide robustness checks for inclusion of that variable in the innovation output and productivity equations.

Identification

Several important econometric issues arise in the estimation of this type of CDM model. The first is the possible sample selection bias due to the fact that only a fraction of the firm population innovates, whereas a large number of firms in the sample are not engaged in R&D activities at all (only 30 per cent of the observations in the final sample have positive R&D values). In addition, the firms may have some kind of innovative effort, but it is not always reported (see Griffith *et al.*, 2006) and some firms may underestimate their R&D (e.g. when it is performed by workers in an informal way).[23] In line with the previous CDM empirical studies, I correct for the selection bias by estimating (1´) and (2´) as a system of equations by maximum likelihood, assuming that the error terms in (1´) and (2´) are bivariate normal with zero mean and covariance matrix as specified in equation (4). In the literature, this model is often referred to as a Heckman selection model (see Heckman, 1979) or type II Tobit model (see Amemiya, 1984). For identification of such a model, the vector x_{it}^{rd} in equation (1´) should contain at least one variable that is *not* in the vector x_{it}^{r} in equation (2´). Nevertheless, all previous works in the CDM literature use the same explanatory variables in both equations. The main reason for this practice is that it is difficult to find the factors explaining a firm's likelihood of engaging in R&D that are not related to the amount of resources the firm decides to invest in R&D. In addition to identification 'by functional form', I use a dummy variable for the firm's previous R&D investments (whether a firm had any R&D activity in the previous 3 years) as an exclusion restriction. On the one hand, I believe that firms that have previous R&D experience have a higher probability of engaging in R&D activities in the given period. On the other hand, it is not obvious that having R&D experience implies higher R&D intensity in the given period (it can happen that 'new' R&D investors, or firms that took a break from investing in R&D, invest more intensively in R&D in the given period than firms that invest

[23] Asheim (2012) points to underreporting of R&D investments and innovation activities in the national R&D statistics as one of the possible explanations for the Norwegian productivity puzzle.

continuously).[24] I elaborate more on the selectivity issues and check for the appropriate choice of explanatory variables and of an 'exclusion restriction', as well as the sensitivity of the results to that choice, in Section 5 when estimating the model.

The second econometric issue refers to the endogeneity of some of the main explanatory variables. Since (1´)-(4´) is a system of recursive equations, it is natural to assume that the main explanatory variable in Equation (4´) (innovation output) is endogenously determined in the previous innovation stage, i.e., in innovation equation (3´); in turn, the main explanatory variable in Equation (3´) (innovation input) is determined in the previous innovation stage, i.e. the R&D intensity equation (2´). The standard CDM model handles this problem of the R&D intensity endogeneity by predicting R&D intensity, r_{it}^{*}, from the estimates of the first block of the model (R&D input decision) and using it as an explanatory variable in the innovation equation (3´). Similarly, to handle the endogeneity of innovation output variable in (4´), the CDM model uses predicted values of innovation output $INNO_{it}^{*}$ from the estimates of the second block of the model as an explanatory variable in the productivity equation (4´).[25] Note that the variables *Market location*, *Part of a group*, *Hampering factors* and *Received subsidy* do not enter directly in the innovation equation (see Table3), but only indirectly through research. Hence, these variables can be used as instruments for the prediction of r_{it}^{*} (this choice is inspired by both Hall *et al.*, 2013, Polder *et al.*, 2009, and Castellacci, 2011). Further, the variables *Cooperation on innovation* and *Purchased R&D*, which are important for innovation output (see Cappelen *et al.*, 2012), are explicitly assumed to only influence productivity indirectly through innovation and are used as instruments for the prediction of innovation output $INNO_{it}^{*}$. These assumptions impose some a priori structure on the model, which is inspired by the previous CDM studies and which helps identification of the model.

One should also keep in mind the possible endogeneity of other explanatory variables, i.e., the *ict* variable in (3´) and the *ictk* and *k* variables in (4´). With respect to the ICT intensity variable, *ict*, in (3´), I follow Hall *et al.* (2013) and use the reported values of ICT investments in year *t* and treat them as exogenous to innovation output. However, I check the robustness of the results by including the lagged ICT capital

[24] The correlation between the *Positive R&D history* variable and the dummy for positive R&D in the given year is 0.65, while the correlation with the R&D intensity variable (r_{it}^{*}) is only -0.01. Note that this variable is equal to zero, both in the case of no R&D activity in the previous 3 years and in the case of missing information on R&D activity in the previous 3 years (about 30 per cent of observations in the final sample). To control for the latter case, I add the dummy variable *No information on R&D history* when estimating (1´).

[25] In case of four different innovation types I generate the predicted probabilities of the $2^4 = 16$ possible combinations of these four types of innovation (all of which exist in my data) and use them as input variables in (4´). The predictions QP1111=Pr*(*pdt*=1,*pcs*=1,*org*=1,*mkt*=1), QP1110= Pr*(*pdt*=1,*pcs*=1,*org*=1,*mkt*=0), etc., correspond to the propensities for the respective combinations [1,1,1,1], [1,1,1,0], etc. Since these add up to one, it is necessary to use one combination as a reference category to avoid perfect collinearity. I use [0,0,0,0] as the reference category.

intensity as an alternative ICT variable in (3´), $ictk_{t-2,}$ (the ICT capital intensity in the start of the corresponding survey period) and also by instrumenting and including the predicted values of the ICT intensity variable, as Polder *et al.* (2009) do. As regards the capital variables *ictk* and *k* in (4´), they are by construction calculated at the beginning of year *t* and, hence, can be treated as predetermined inputs relative to productivity in the year *t*.

Next, since I have a panel data set (pooled data from the four waves of the innovation survey: CIS2004, CIS2006, CIS2008 and CIS2010), it is important to think about an appropriate panel estimation strategy. However, there are few firms with more than one firm-year observation (about 60 per cent of firms are represented only once in the sample, with the average number of observations per firm being 1.6). I therefore pool all firm-year observations and, for each of the four equations, adjust the standard errors for clustering at the firm level.

Finally, the timing of the questions in the survey is such that one cannot really claim a direct causal relationship between R&D and ICT investment, on the one hand, and innovation, on the other, since the latter is measured over the preceding three years in the questionnaire, while R&D and ICT investment are measured in the year of the questionnaire. The reported results should therefore be viewed as representing associations rather than causal relationships.

5. Empirical results

This section presents the estimation results of the augmented CDM model. The first model block (R&D input decision) is estimated using the whole sample. Since we can expect that the importance of R&D and ICT to differ between industries, the second (Innovation output) and third (Productivity) model blocks are estimated both for the whole sample and separately for manufacturing and services.

5.1 Estimation results of model block 1: R&D input decision

I first test for selection in R&D reporting and use the same test as in Hall *et al.* (2013), where one first estimates a probit model where the presence of positive R&D expenditures depends on a set of defined firm characteristics. After having estimated this model, one can, for each firm, recover the predicted probability of having R>0 and the corresponding Mills' ratio. Then I estimate a simple linear (OLS) for R&D intensity, adding to this equation the predicted probabilities from the R&D decision equation, the Mills' ratio, their squares and an interaction term between the predicted probabilities and Mill's ratio as regressors. The presence of selectivity bias is then tested for by looking at the significance of these 'control functions'.[26] The results of this test are reported as model (1) in Table 4. The predicted probability terms are jointly significant,

[26] This procedure is a generalisation of Heckman's two-step procedure for estimation when the error terms in the two equations are jointly normally distributed. The test here is a semi-parametric extension for non-normal distributions.

with a $\chi^2(5)$ = 11.41. I therefore conclude that selection bias is present in my data on R&D and estimate the first model block as a system of two equations by maximum likelihood.

Table 4 – Estimation results – Sample selection model for R&D choice

	(1)		(2)		(3)		(4)	
	Probit	OLS	Sample selection		Sample selection		Sample selection	
Dependent variables:	Prob. of R>0	Log R&D per empl.	Prob. of R>0	Log R&D per empl.	Prob. of R>0	Log R&D per empl.	Prob. of R>0	Log R&D per empl.
Log employment	0.096	-0.817***	0.104	-0.765***	0.429***	-0.624***	0.391***	-0.666***
	[0.063]	[0.096]	[0.063]	[0.096]	[0.070]	[0.094]	[0.075]	[0.094]
Log employment squared	0.004	0.038***	0.003	0.036***	-0.015*	0.028**	-0.015	0.030***
	[0.007]	[0.011]	[0.007]	[0.011]	[0.009]	[0.011]	[0.009]	[0.011]
H: high costs	0.283***	-0.095***	0.280***	-0.053**	0.340***	0.021	0.237***	-0.011
	[0.018]	[0.024]	[0.018]	[0.023]	[0.017]	[0.024]	[0.020]	[0.022]
H:lack of qualified personal	0.136***	0.064***	0.136***	0.084***	0.173***	0.120***	0.155***	0.104***
	[0.021]	[0.023]	[0.021]	[0.022]	[0.020]	[0.022]	[0.025]	[0.022]
H:lack of information	0.111***	-0.038	0.111***	-0.023	0.121***	0.001	0.091***	-0.010
	[0.024]	[0.027]	[0.024]	[0.026]	[0.022]	[0.026]	[0.028]	[0.026]
Market location: National	0.330***	0.203***	0.331***	0.245***	0.456***	0.358***	0.324***	0.311***
	[0.035]	[0.052]	[0.035]	[0.052]	[0.034]	[0.052]	[0.041]	[0.050]
Market location: European	0.523***	0.370***	0.521***	0.461***	0.739***	0.626***	0.577***	0.558***
	[0.054]	[0.070]	[0.053]	[0.068]	[0.054]	[0.069]	[0.063]	[0.066]
Market location: World	0.612***	0.591***	0.601***	0.702***	0.833***	0.875***	0.691***	0.802***
	[0.063]	[0.076]	[0.062]	[0.075]	[0.062]	[0.077]	[0.077]	[0.072]
Part of a group	-0.047	0.104**	-0.046	0.103**	-0.023	0.099**	-0.034	0.101**
	[0.035]	[0.046]	[0.035]	[0.046]	[0.034]	[0.046]	[0.041]	[0.046]
Cooperation in R&D		0.235***		0.241***		0.251***	1.361***	0.251***
		[0.039]		[0.039]		[0.039]	[0.049]	[0.039]
Received subsidies		0.711***		0.719***		0.738***	3.198***	0.737***
		[0.041]		[0.041]		[0.041]	[0.139]	[0.054]
<u>Exclusion restriction:</u>								
Positive R&D history	1.719***		1.732***					
	[0.042]		[0.042]					
No info. on R&D history	0.423***		0.438***					
	[0.045]		[0.045]					
Chi-square for selection		11.41***		27.17***		10.18***		0.00
Correlation coefficient rho				-0.239***		0.138***		-0.001
Log likelihood	-4581.74			-11294.48		-12496.10		-10362.24
Number of obs. (uncensored)	14533	4377		14533(4377)		14533(4377)		14533(4377)

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Models (2)-(4) differ by the sets of explanatory variables in the selection equation for R&D and are estimated by maximum loglikelihood using Heckman procedure in Stata.
*** p<0.01, ** p<0.05, * p<0.1

The results of model (2) in Table 4 support the presence of selection with a highly significantly estimated correlation coefficient ρ of almost -0.24. As expected, the *R&D investment history* variable has a positive impact on the propensity to invest in R&D, indicating the extent of *persistency* in the firms' R&D policy. This variable seems to be correlated with the firm size variable, which is not significant when the *R&D investment history* is controlled for (see coefficients for *Employment* in model (2) and models (3) and

(4) in Table 4 for comparison).[27] This is probably due to the fact that larger firms invest more often in R&D than smaller firms. The exclusion of the *Positive R&D history* variable in the selection equation changes the sign of the estimated correlation coefficient ρ between the regression error and selection error terms, resulting in the opposite direction of selection bias (comparing models (2) and (3) in Table 4). If, in addition, I use the same explanatory variables in both the selection and R&D intensity equations (as in Hall *et al.*, 2013), the Heckman procedure fails to identify the selection bias in my data (see the results fo model (4) in Table 4).[28] This is possibly because the *Received subsidies* variable used here can differ from the similar one used in Hall *et al.* (2013), i.e. their variable covers subsidies for investments in general, while my variable only covers subsidies for R&D. As a result, receiving a subsidy automatically implies R>0 and, hence, leads to the extremely high estimated coefficient for the *Received subsidies* variable in the selection equation of model (4) in Table 4 and to the collinearity problems in the R&D intensity equation (see Stolzenberg and Relles, 1997).[29] Stolzenberg and Relles (1997) also noted that a downward-biased estimate could be quite useful for testing a substantive hypothesis of a positive impact of the variable of interest (then we might reasonably conclude that a lower-bound estimate of the corresponding coefficient has been found). Keeping that in mind, I use model (2) in Table 4 as my basic specification, since this model gives the 'lowest' estimated coefficients for the main predictors of R&D intensity.

The results for the other explanatory variables in the basic model specification (model (2) in Table 4) are in line with the previous results in the CDM model literature. A firm's international orientation (reflected by main product market location variables) is positively correlated with the probability that the firm is engaged in R&D, confirming the close relationship between technological capabilities and export propensity that has previously been established in the literature (Aw *et al.*, 2007). Belonging to a group does not influence the propensity to invest in R&D. Finally, the regression results indicate a positive and significant relationship between the three hampering factor variables – high costs, lack of qualified personnel and access to information – and the propensity to engage in R&D. In line with the previous CDM works, this is interpreted as an indication of the relevance of these variables as factors shaping the innovative process.

For comparison with the R&D equation, I also estimate the corresponding models (with and without controlling for selection) for ICT investment (see models (3) and (4) in Table C1). The specification is the same as for R&D investment with one exception: I use a dummy for positive ICT capital lagged two years,

[27] Models (2)–(4) differ only by the set of explanatory variables in the selection equation for R&D, with model (3) and model (4) being similar to those in Polder *et al.*, 2009, and Hall *et al.*, 2013, correspondingly.

[28] The further use of the predictions for the R&D intensity from this model specification also resulted in lack of convergence of the likelihood function for the zero-inflated model when analysing the data on patent applications.

[29] By simulations, Stolzenberg and Relles (1997) demonstrate that the well-known two-step Heckman estimation procedure is not a universal procedure against the selection bias problem, since it can both increase and decrease the accuracy of regression coefficient estimates. So, the choice of the explanatory variables for the estimation of sample selection model seems to be important.

$ictk_{t-2}$, as a *Positive investment history* variable in the selection equation for ICT. As expected, the reported bias or selection is not an important issue for this kind of investment, both because ICT is an instance of a ‘general purpose technology’ that can be easily bought and because it is less subject to market failure than R&D. ICT is also less plagued by uncertainty and more easily tracked.[30] Hence, models (3) and (4) yield identical results for ICT intensity. Like R&D, ICT intensity increases with the firm’s international orientation (communication possibilities become more important when a firm is engaged in activities abroad), but its impact on ICT intensity is lower. Group membership (better internal access to sources of financing), cooperation on innovation and the magnitude of the hampering factor ‘lack of qualified staff’ (in both cases, communication possibilities are vital) also have a positive impact on ICT intensity. Interestingly, receiving subsidies (which are R&D investment subsidies) increases ICT investment by 14 per cent on average, probably due to the fact that more financial resources become available for other types of investment when a firm receives a subsidy for carrying out R&D. In contrast to R&D intensity, ICT intensity increases with firm size in Norwegian firms (in contrast to what has been found for Italian firms by Hall *et al.*, 2013). Both R&D and ICT intensities vary with firm age, industry and location, and with time.

Based on the results of Table C1, which explores the selection issues of R&D and ICT reporting, and following Hall *et al.* (2013), in the next section of the paper, I use the predicted values of R&D intensity (the expectation of R&D intensity conditional on the other firm characteristics) and the reported values for ICT investment intensity to explain the propensity for different types of innovation and number of patent applications. I further explore the possible endogeneity of the reported ICT intensity and check the robustness of the results by including the lagged ICT capital as an input in the innovation output equation, i.e. ICT capital at the start of the corresponding survey period, or by instrumenting and including the predicted values of the ICT intensity variable (based on model (4) in Table C1), as Polder *et al.* (2009) do.

5.2 Estimation results of model block 2: Innovation output

Tables 5–7 report the results of estimation of innovation output equations (3a´) – (3c´) for different innovation output proxies (any type of innovation, four types of innovation and number of patent applications) and for three different samples of the firms (all firms, firms in manufacturing and firms in service industries).

Measuring innovation output with one dummy for any type of innovation

Table 5 reports the results of the simple probit model estimation of equation (3a´) for any type of innovation and for all three samples of the firms under investigation. I present these results first, mainly to compare them

[30] Roughly 90 per cent of observations on ICT investment are positive, compared to 30 per cent of positive observations on R&D.

with those obtained by Hall *et al*. (2013), who use the model specification for any type of innovation as their main specification. In addition, I provide different robustness checks for this case. From Table 5, we can see that, irrespective of the sample, the propensity to innovate has a similar relationship to the main explanatory variables, increasing strongly with R&D and ICT intensities, the share of high-skilled workers and firm size. In addition to the positive impact of ICT intensity, not having any ICT investment at all is negative for the propensity to innovate.[31] However, the impact of ICT intensity is substantially lower than the impacts of R&D intensity and share of high-skilled man-hours, indicating that the latter two factors are relatively more important for innovation than ICT (this result is in line with those obtained by Hall *et al.*, 2013). Interestingly, while R&D intensity is of similar importance for innovation in both industries, skills and ICT intensity are relatively more important for innovation in manufacturing. Given much lower levels of ICT intensity in manufacturing (measured both as ICT capital services per value added and as ICT investment per employee, ref. Table 2), the latter finding suggests the conclusion that Norwegian manufacturing firms may be underinvesting in ICT compared to firms in service industries.

Table 5 – Estimation results – Innovation output: Any type of innovation (by industry)

Sample:	All firms			Manufacturing			Services		
	Coeff.	S.e.	Btstr.	Coeff.	S.e.	Btstr.	Coeff.	S.e.	Btstr.
Log R&D intensity (predicted)	0.836 ***	0.043	(0.041)	0.803 ***	0.063	(0.056)	0.812 ***	0.062	(0.061)
Share of high skilled	0.500 ***	0.076	(0.072)	0.780 ***	0.143	(0.129)	0.385 ***	0.096	(0.083)
Log ICT intensity	0.046 ***	0.010	(0.010)	0.074 ***	0.018	(0.016)	0.026 *	0.015	(0.015)
Zero ICT investment	-0.125 ***	0.044	(0.042)	-0.165 ***	0.066	(0.063)	-0.118 *	0.073	(0.065)
Log employment	0.749 ***	0.059	(0.051)	0.812 ***	0.096	(0.084)	0.678 ***	0.086	(0.074)
Log employment squared	-0.030 ***	0.007	(0.006)	-0.040 ***	0.012	(0.010)	-0.026 ***	0.010	(0.008)
Cooperation: National	0.564 ***	0.050	(0.043)	0.567 ***	0.071	(0.069)	0.523 ***	0.077	(0.075)
Cooperation: Scandinavia	0.335 ***	0.100	(0.093)	0.448 ***	0.140	(0.124)	0.294 *	0.162	(0.162)
Cooperation: EU	0.026	0.097	(0.118)	0.142	0.150	(0.147)	-0.044	0.143	(0.145)
Cooperation: World	0.198	0.121	(0.130)	0.249	0.221	(0.202)	0.289 *	0.166	(0.176)
Purchased R&D	0.622 ***	0.052	(0.048)	0.663 ***	0.068	(0.066)	0.590 ***	0.088	(0.073)
Number of observations	14533			6199			6145		
Non-zero observations	6967			3412			2997		
Log likelihood	-7804.49			-3234.75			-3459.13		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and for the whole sample, mature firms (16 years old or older)) in the capital region (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level. Bootstrap standard errors (in brackets) are based on 100 replications.
Dependent variable: binary indicator for any type of innovation. Estimated by maximum loglikelihood as a probit model in Stata.
*** p<0.01, ** p<0.05, * p<0.1

[31] About 10 per cent of observations on ICT investment are zeros. Since the log of the ICT investment intensity is used in the empirical specification (and, as a consequence, firms with zero ICT investment would turn into missing observations), I convert missing log-values to zeros and add a dummy variable for zero ICT investment.

As for other explanatory variables, cooperation on innovation (at the national and Scandinavian level) and the purchasing of R&D from external providers are also strongly associated with innovation, in both manufacturing and service industries. These results suggest that the external acquisition of knowledge from specialised service providers represents an important complementary strategy through which firms are able to improve their innovative performance. The latter result is in line with those obtained earlier based on Norwegian data by Cappelen *et al.* (2012), who show that firms collaborating with others on their R&D are more likely to be successful in their innovation activities, including patenting.

As mentioned earlier, I use the predicted R&D intensity in the analysis of the innovation equation in the CDM model. Using the predicted values for R&D intensities instead of the observed values is a sensible way to instrument the innovative effort in the knowledge production function in order to deal with simultaneity problems between R&D investment and innovative outcomes. However, given that the model is estimated sequentially, conventional standard error estimates will be biased. Therefore, Table 5 also presents bootstrap standard errors based on 100 replications. In general, we can see that bootstrapping makes relatively little difference to the standard errors and the significance levels. Hall *et al.*, 2013, and Polder *et al.*, 2009, obtain the same results for bootstrapping of standard errors in their analysis.[32]

Robustness checks for inclusion of skill variable in the innovation output equation

I check for the robustness of these results with respect to the exclusion of a skill variable and with respect to the inclusion of an interaction term between R&D intensity and a skill variable (again in order to compare my results with those in Polder *et al.*, 2009, who do not use a skill variable and with those in Hall *et al.*, 2013, who check for the importance of an interaction term for their sample of manufacturing firms). The results by industry are presented in Table C2. The impacts of R&D and ICT intensities remain positive and highly significant, irrespective of the inclusion or exclusion of the skill variable. In contrast to Hall *et al.* (2013), the inclusion of an interaction term does not show evidence of complementarity between skills and R&D intensity in manufacturing, while the estimated effect of the interaction term is positive and highly significant in service industries. The estimates of the other coefficients in the basic model are largely unchanged by the addition of these variables.

Exploring endogeneity of ICT variable in the innovation output equation

In order to check for possible endogeneity of the ICT intensity variable in the innovation output equation (since I use the observed ICT intensity in period *t*), I first re-estimate equation (3a´) by using the ICT capital intensity lagged two years as an input ICT variable, $ictk_{t-2}$ (the log of ICT capital per employee at the start of

[32] All further results are also robust to bootstrapping of standard errors, but are only reported with conventional standard errors.

the corresponding survey period). Then I re-estimate equation (3a´) by instrumenting and including the predicted values of the ICT intensity variable based on model (4) in Table C1 (as Polder *et al.*, 2009, do). The results are presented in Table C3, where model (1) corresponds to the basic model with the observed ICT intensity, model (2) corresponds to the use of the lagged ICT intensity and model (3) corresponds to the use of the predicted ICT intensity. The use of the lagged ICT capital intensity marginally changes the main results (compare the results for model (1) to those for model (2) in Table C3). Furthermore, using the predicted ICT investment intensity together with the predicted R&D intensity results in a substantial reduction in the impact of the R&D intensity variable and a huge increase in the impact of the ICT intensity variable.[33] I interpret these results as a manifestation of the limitations of instrumenting two somewhat similar variables using the same set of predictors. This can lead to a multicollinearity problem in the innovation output equation. I further conclude that the potential endogeneity problem of the observed ICT intensity variable is not crucial to the results and proceed to analyse other measures of innovation output using my basic specification (with the observed ICT intensity).

Measuring innovation output with dummies for four different innovation types

Table 6 reports the estimation results of the quadrivariate probit model (3b´) when the innovation output is measured with dummies for four different types of innovation (product, process, organisational and marketing innovation). To explore the hypothesis that the importance of innovation modes can differ between industries, Table 6 only focuses on the results for the manufacturing firms and firms in services (the results for the whole sample are presented in Table C4).[34]

Firstly, we can see that the independence of the error terms across equations in (3b´) is rejected, with highly significant values in a χ^2-test for all rho equal to zero[35] ($\chi^2(6)$=1382.10 and $\chi^2(6)$=1749.67 for the sample of manufacturing firms and firms in services, respectively). All four innovation types have similar relationships to the main explanatory variables, increasing strongly with the R&D and ICT intensities, the share of high-skilled workers and firm size. More specifically, the results confirm earlier findings that ICT is

[33] In Polder *et al.* (2009), the R&D intensity is even insignificant for the innovation output in most of the cases (one exception is product innovation in manufacturing firms), which appears to be an unusual result in the CDM literature, while the estimated coefficients of the predicted ICT intensity are very high.

[34] The estimation is done in Stata using the program *mvprobit* (see Cappellari and Jenkins, 2003) with the number of draws for the GHK simulator equal to 80 for the sample of manufacturing firms and firms in services, and to 120 for the whole sample. As documented in Cappellari and Jenkins (2003), the number of random draws, which is approximately equal to the square root of the sample size, is sufficiently large to simulate estimates that are similar to the corresponding ML estimates. For the prediction and further use of joint probabilities for four innovation types QP1111=Pr*(*pdt*=1, *pcs*=1, *org*=1, *mkt*=1), QP1110= Pr*(*pdt*=1, *pcs*=1, *org*=1, *mkt*=0) etc., I adopted and re-programmed the estimation routines from the Stata program *mvped* (that only predicts 'all successes', QP1111, and 'all failures', QP0000) in order to get all 16 combinations.

[35] This is the test that all correlations $\rho_{jk} = \rho_{kj}$ between η^k and η^j in (3b´), $j,k = 1,2,3,4$ and $j \neq k$, are jointly equal to zero.

relatively more important for product innovation in manufacturing and for process innovation in service industries (see, for instance, Vincenzo, 2011). Not having any ICT investment at all is strongly negative for process and organisational innovation in manufacturing firms and for product and marketing innovation in firms in the service sector.

Table 6 – Estimation results – Innovation output: Four types of innovation (manufacturing firms versus firms in services)

Innovation type:	New product		New process		Organisational		Marketing	
	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
Manufacturing firms (6199 observations, 3386 firms)								
Log R&D intensity (predicted)	0.800 ***	0.061	0.598 ***	0.059	0.165 ***	0.057	0.360 ***	0.054
Share of high skilled	0.814 ***	0.150	-0.038	0.154	0.389 ***	0.149	0.453 ***	0.138
Log ICT intensity	0.089 ***	0.019	0.043 **	0.018	0.048 ***	0.019	0.053 ***	0.018
Zero ICT investment	-0.068	0.074	-0.286 ***	0.075	-0.169 **	0.081	-0.050	0.070
Log employment	0.708 ***	0.103	0.419 ***	0.096	0.971 ***	0.090	0.433 ***	0.087
Log employment squared	-0.032 **	0.012	-0.013	0.011	-0.073 ***	0.010	-0.028 ***	0.010
Cooperation: National	0.504 ***	0.064	0.484 ***	0.059	0.419 ***	0.059	0.467 ***	0.057
Cooperation: Scandinavia	0.162 *	0.098	0.348 ***	0.080	0.270 ***	0.079	0.245 ***	0.080
Cooperation: EU	0.227 **	0.102	0.024	0.085	0.043	0.083	0.007	0.090
Cooperation: World	-0.184 *	0.109	-0.078	0.103	0.031	0.096	-0.109	0.097
Purchased R&D	0.490 ***	0.058	0.299 ***	0.056	0.206 ***	0.054	0.248 ***	0.055
Non-zero observations	2217		1590		1467		1848	
Chi-square for all rho=0	1382.10 ***							
Log likelihood	-11292.29							
Firms in services (6145 observations, 3947 firms)								
Log R&D intensity (predicted)	0.953 ***	0.063	0.457 ***	0.060	0.316 ***	0.058	0.378 ***	0.058
Share of high skilled	0.592 ***	0.104	0.083	0.102	0.221 **	0.108	0.169 *	0.097
Log ICT intensity	0.035 **	0.017	0.042 **	0.016	0.037 **	0.016	-0.001	0.015
Zero ICT investment	-0.153 *	0.091	0.061	0.085	0.043	0.088	-0.190 **	0.077
Log employment	0.493 ***	0.087	0.247 ***	0.089	1.295 ***	0.098	0.274 ***	0.079
Log employment squared	-0.007	0.010	0.002	0.010	-0.100 ***	0.011	-0.009	0.009
Cooperation: National	0.451 ***	0.071	0.430 ***	0.068	0.275 ***	0.066	0.413 ***	0.066
Cooperation: Scandinavia	0.186	0.116	0.203 *	0.112	0.189 *	0.098	0.208 **	0.102
Cooperation: EU	0.066	0.110	-0.148	0.107	0.095	0.102	0.095	0.098
Cooperation: World	0.108	0.139	0.194 *	0.117	0.064	0.100	0.172 *	0.102
Purchased R&D	0.535 ***	0.072	0.370 ***	0.067	0.244 ***	0.066	0.175 ***	0.067
Non-zero observations	1827		1327		1330		1677	
Chi-square for all rho=0	1749.67 ***							
Log likelihood	-10356.82							

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services, mature firms (16 years old or older)) in the capital region (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level.
Dependent variables: binary indicators for different types of innovation. Estimated as a quadrivariate probit model by use of program *mvprobit* in Stata (see Cappellari and Jenkins, 2003) with number of draws for the GHK simulator equal to 80.
*** p<0.01, ** p<0.05, * p<0.1

As regards other explanatory variables, cooperation with others at the national and Scandinavian level (for all types of innovation in both industries), at the European level (for product innovation in manufacturing) and at the world level (for process and marketing innovation in services), together with purchasing R&D services from external providers, are positively related to the propensity to innovate. While cooperation on innovation seems to be relatively more important for innovation in manufacturing, purchasing R&D from external providers has a higher impact on most types of innovation in services.

Measuring innovation output by the number of patent applications

Table 7 reports the results by industry for estimation of equation (3c´), where another proxy of innovation output is used, i.e. the number of patent applications. Since numbers of patent applications are observed as integer numbers with many zero observations, we can model them as zero-inflated count data and use pseudo maximum likelihood for the estimation.[36] In this model, I use a binary indicator for any type of innovation, *inno*, as a main inflate variable, since only innovative firms can apply for a patent. In addition, the inflation equation includes firm age, industry and location, and time dummies, since we can expect a higher/lower probability of applying for a patent for some age groups, regions and industries. I use a count model specification with negative binomial distribution, since the Poisson distribution imposes equality of the variance and the mean of the count data. That is not the case for my patent applications data (see Table A2). As shown by the results in Table 7, the dispersion parameter alpha is far from zero, so the negative binomial (NB) specification is preferable to the Poisson specification. A Vuong test compares the zero-inflated NB model to a standard NB model. With a highly significant Vuong test value, I reject the standard NB model specification and conclude that the zero-inflated NB model is a proper count data model specification for my data.

Turning to the estimation results themselves, they are in line with the results for the main variables for innovation, i.e. R&D intensity and workers' skills are strongly associated with patenting, in both manufacturing and service industries, with R&D being more important for patenting in service industries and skills being relatively more important for patenting in manufacturing. ICT intensity also has a positive impact on patenting, but, again, this impact is substantially lower than the impacts of R&D intensity and the share of high-skilled man-hours. Interestingly, in contrast to the results for innovations, the estimated coefficient for zero ICT investment is positive and significant. However, when I re-estimate the model for patent applications with ICT capital lagged two years (see column (5) in Table C3), the ICT variables become insignificant, while re-estimation with the predicted values of the ICT intensity (see column (6) in Table C3) makes the ICT intensity highly significant and more important for patenting than the R&D intensity. Such instability in the results for the ICT variable indicates that strong conclusions cannot be drawn concerning the impact of ICT on patenting, while the results for other explanatory variables are robust to different model

[36] My intuition when choosing a zero-inflated count data model instead of a standard count data model for the patent data analysis is based on the existence of two groups, i.e. the 'always zero group' (those who never innovate and, hence, have no reason to apply for a patent) and the 'not always zero group' (those who innovate, but do not always apply for a patent). The estimation is done in Stata using the *zinb* procedure.

specifications. Cooperation on innovation and the purchase of R&D services from external providers are also positively related to the number of patent applications, but, in contrast to the results for different innovation types, where cooperation at the national and Scandinavian levels was important, cooperation at the European and world levels is more important for patenting.

Table 7 – Estimation results – Innovation output: Number of patent applications (by industry)

Sample:	All firms		Manufacturing		Services	
Log R&D intensity (predicted)	0.898***	[0.093]	0.419***	[0.120]	1.500***	[0.142]
Share of high skilled	1.656***	[0.219]	2.190***	[0.310]	1.159***	[0.307]
Log ICT intensity	0.086***	[0.030]	0.104***	[0.037]	0.077*	[0.046]
Zero ICT investment	0.408***	[0.158]	0.282	[0.174]	0.446*	[0.264]
Log employment	1.145***	[0.153]	0.663***	[0.238]	1.983***	[0.251]
Log employment squared	-0.031**	[0.016]	0.010	[0.022]	-0.108***	[0.026]
Cooperation: National	0.039	[0.088]	0.152	[0.104]	-0.074	[0.158]
Cooperation: Scandinavia	0.041	[0.101]	-0.018	[0.120]	0.158	[0.191]
Cooperation: EU	0.241**	[0.104]	0.275**	[0.126]	0.187	[0.187]
Cooperation: World	0.176	[0.113]	0.217	[0.142]	-0.051	[0.207]
Purchased R&D	0.369***	[0.080]	0.339***	[0.097]	0.405***	[0.137]
Inflation (any innovation)	-35.659***	[2.977]	-5.598***	[1.912]	-53.474***	[3.156]
Log likelihood	-4724.486		-2694.006		-1726.743	
Alpha for NB vs Poisson specification	1.24		0.89		1.67	
Vuong test for zero inflated specification	8.38***		5.36***		5.09***	
Number of observations (non-zero)	14533(1467)		6392 (900)		6145(503)	

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and for the whole sample, mature firms (16 years old or older)) in the capital region (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level.
Estimated by pseudo maximum loglikelihood as a zero inflated negative binomial (NB) count data model.
*** p<0.01, ** p<0.05, * p<0.1

5.3 Estimation results of model block 3: Productivity

In the last part of the analysis I look at the productivity impacts of innovation activities.

Exploring the importance of innovation, ICT and human capital for productivity

Tables 8–9 show OLS-estimates of equation (4´) by industry with and without measures of ICT capital intensity and the skill variable (while Hall *et al.*, 2013, control for the ICT intensity in the productivity equation, but not for the skill composition in the firm, Polder *et al.*, 2009, do not include any of these two variables at the last block of the CDM model). Table 8 shows that, when I proxy innovation with the predicted probability of any innovation conditional on R&D, ICT and the other firm characteristics, I find a positive effect of innovation on productivity, i.e. the introduction of any type of innovation increases productivity by approximately 8 per cent independently of the estimation sample (columns (1) of Table 8). Nevertheless, when I include the ICT capital intensity in the productivity equation (columns (2) of Table 8), the predicted probability of innovation activity loses a substantial part of its impact. ICT capital services per employee appear to be a much better predictor of productivity gains than the probability of innovation predicted by ICT and R&D investments. When I also include the skill variable, the ICT capital coefficient decreases slightly, while the innovation coefficient becomes very low (but still significant) for manufacturing firms and even insignificant for the whole sample and firms in service industries (columns (3) of Table 8). The latter result is in line with those in Crepon *et al.* (1998), who also observe a substantial decrease in the estimated elasticity of knowledge capital for manufacturing firms when the skill variable is included in the productivity equation. These results indicate that both ICT and skills are important inputs to a firm's productivity and should not be ignored when analysing the effects of innovations on productivity and economic growth.[37]

Table 8 – Estimation results – Productivity: with any type of innovation (by industry)

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Probability of any	0.086***	0.052***	0.012*	0.081***	0.043***	0.012*	0.078***	0.045***	-0.015
innovation (predicted)	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.012]	[0.012]	[0.012]
Log ICT capital		0.107***	0.092***		0.117***	0.102***		0.110***	0.096***
per employee		[0.005]	[0.005]		[0.006]	[0.006]		[0.007]	[0.007]
Share of high skilled			0.472***			0.491***			0.520***
			[0.031]			[0.045]			[0.035]
Log tangible capital	0.097***	0.076***	0.086***	0.095***	0.078***	0.087***	0.097***	0.070***	0.081***
per employee	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Log employment	0.114***	0.102***	0.107***	0.095***	0.081***	0.088***	0.130***	0.116***	0.115***
	[0.020]	[0.019]	[0.019]	[0.024]	[0.023]	[0.022]	[0.026]	[0.025]	[0.024]
Log employment squared	-0.010***	-0.008***	-0.008***	-0.005*	-0.002	-0.003	-0.015***	-0.012***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
R-squared	0.24	0.28	0.30	0.29	0.34	0.36	0.16	0.21	0.24
Number of observations	14427			6162			6086		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and, for the whole sample, mature firms (16 years old or older)) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
*** p<0.01, ** p<0.05, * p<0.1

Table 9 reports the OLS estimation results for the productivity analysis when the predicted number of patent applications per employee is used as a proxy for innovation. The estimated semi-elasticities of the

[37] However, these results can also be a reflection of the high correlation between knowledge capital (predicted by the R&D and ICT intensities, which are highly correlated with the skill variable, as seen from Table A3) and the skill variable. This correlation raises the delicate problem of whether knowledge capital and skills are substitutable or complementary factors. In the former case, lower estimates (when controlling for skill composition) are the appropriate ones, while, if the latter is true, and in the extreme case where knowledge capital and skills are perfect complements, the higher estimates (when not controlling for skill composition) would be the right ones. Earlier robustness checks of the innovation output equation (see Table C2) did not show evidence of complementarity between skills and R&D intensity in manufacturing, while the estimated effect of the interaction term between R&D intensity and the skill variable is positive and highly significant in service industries, implying that the results from columns (3) in Table 8 are more appropriate for manufacturing firms, and from columns (2) in Table 8 (when not controlling for skill composition) for firms in service industries. However, for firms in service industries, this would mean that increases in a firm's research efforts and knowledge capital do not by themselves result in increased productivity, but must be accompanied by related increases in skills.

number of patent applications per employee are high and significant, being about 0.80 for manufacturing firms, 0.24 for firms in service industries and 0.33 for the whole sample (columns (1) of Table 9). [38] While the inclusion of the ICT variable slightly reduces the impact of the patent variable (columns (2) of Table 9), if the skill variable is included in addition (columns (3) of Table 9), the patent variable loses (almost) all its significance, with the exception of manufacturing firms, where the corresponding semi-elasticity remains positive, significant and relatively high (0.22 compared to 0.09 in Crepon *et al.*, 1998, for French manufacturing firms), indicating that patenting is relatively more important for increasing productivity in manufacturing, while skills are relatively more important for productivity in service industries.

Table 9 – Estimation results – Productivity: with the number of patent applications per employee (by industry)

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Number of patent appl.	0.331***	0.240***	-0.053	0.801***	0.606***	0.220**	0.240***	0.201***	-0.033
per empl. (predicted)	[0.059]	[0.057]	[0.056]	[0.098]	[0.093]	[0.096]	[0.066]	[0.064]	[0.063]
Log ICT capital		0.112***	0.093***		0.122***	0.104***		0.113***	0.095***
per employee		[0.005]	[0.005]		[0.006]	[0.006]		[0.007]	[0.007]
Share of high skilled			0.496***			0.475***			0.510***
			[0.031]			[0.045]			[0.034]
Log tangible capital	0.101***	0.077***	0.086***	0.101***	0.081***	0.087***	0.098***	0.070***	0.081***
per employee	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Log employment	-0.020	0.001	0.134***	-0.216***	-0.161***	-0.001	0.027	0.024	0.128***
	[0.036]	[0.034]	[0.032]	[0.045]	[0.043]	[0.043]	[0.041]	[0.040]	[0.039]
Log employment squared	0.004	0.003	-0.010***	0.028***	0.023***	0.006	-0.005	-0.003	-0.013***
	[0.004]	[0.004]	[0.003]	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
R-squared	0.23	0.27	0.30	0.28	0.34	0.36	0.16	0.21	0.24
Number of observations	14427			6162			6086		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and, for the whole sample, mature firms (16 years old or older)) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
*** p<0.01, ** p<0.05, * p<0.1

Exploring the importance of different innovation types for productivity

Table 10 presents the OLS estimation results (by industry) for the production function, where the skill variable is included and where the predicted propensities for the combinations of different innovation types are used as a proxy for innovation, based on a quadrivariate probit estimation of (3b´). The results in Table 10 show that product innovation (alone or in combination with marketing innovation) has a positive impact on productivity in manufacturing (while estimated coefficients for both QP1000 and QP1001 are positive and highly significant, the estimated coefficient for QP0111 is negative and highly significant).

[38] These semi-elasticities mean, for example, that the difference between the last and first decile in the number of patent applications (from 1 to 3) corresponds to 8.7 per cent higher productivity for the patenting manufacturing firms, and to 3.4 per cent higher productivity for patenting firms in service industries (the author's calculations based on distributions for firm size and the number of patent applications for innovative firms).

While process and organisational innovations seem to be important for productivity in service industries (the estimated coefficients for QP0100 and for both QP0010 and QP0011 are positive and highly significant, while the estimated coefficient for QP1101 is negative and highly significant).[39] These results are also reflected in the results for the whole sample of firms (where the Construction industry and some other small industries are included). Interestingly, the introduction of all types of innovation together has a positive but relatively low impact on productivity, compared to the introduction of product innovation (alone or in combination with marketing innovation) in manufacturing and process or organisational innovation in services.

Table 10 – Estimation results – Productivity: with combinations of four innovation types (by industry)

Sample:	All firms		Manufacturing		Services	
QP1111 (predicted)	0.441**	[0.175]	0.096	[0.230]	0.375	[0.230]
QP1110 (predicted)	0.907	[0.674]	0.694	[0.727]	1.368	[0.950]
QP1101 (predicted)	-1.162***	[0.312]	-0.472	[0.417]	-0.868**	[0.364]
QP1011 (predicted)	-0.296	[0.674]	0.974	[0.909]	-0.387	[0.802]
QP0111 (predicted)	-1.569	[1.276]	-3.164**	[1.350]	-2.487	[1.848]
QP0011 (predicted)	1.126	[0.888]	0.961	[1.139]	2.035*	[1.107]
QP0101 (predicted)	1.449	[1.716]	3.059	[1.867]	-0.104	[2.107]
QP0110 (predicted)	0.100	[0.871]	1.500	[1.044]	-0.410	[1.349]
QP1001 (predicted)	1.713***	[0.472]	1.294**	[0.545]	0.974	[0.667]
QP1010 (predicted)	-0.663	[1.089]	-3.232**	[1.456]	1.485	[1.542]
QP1100 (predicted)	-1.178**	[0.504]	-1.323**	[0.663]	-0.589	[0.587]
QP0001 (predicted)	-0.706	[0.475]	-0.647	[0.567]	-0.891	[0.563]
QP0010 (predicted)	0.237	[0.299]	-0.455	[0.531]	0.685*	[0.396]
QP0100 (predicted)	1.218*	[0.644]	-0.641	[0.583]	4.855***	[0.909]
QP1000 (predicted)	0.503*	[0.278]	0.753***	[0.291]	-0.167	[0.417]
ICT capital intensity	0.090***	[0.005]	0.100***	[0.006]	0.088***	[0.007]
Tangible capital intensity	0.085***	[0.004]	0.086***	[0.005]	0.080***	[0.005]
Share of high skilled	0.411***	[0.042]	0.355***	[0.065]	0.535***	[0.041]
Log employment	0.075**	[0.034]	0.088**	[0.039]	0.034	[0.050]
Log employment squared	-0.006*	[0.003]	-0.002	[0.004]	-0.007	[0.005]
R-squared	0.30		0.36		0.25	
Number of observations	14427		6162		6086	

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and, for the whole sample, mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
QP refers to the combinations of the Quadrivariate Probit model for four innovation types: product, process, organisational and marketing innovation, e.g. QP1001 refers to the combination [1,0,0,1], i.e. the firm has introduced both product and marketing innovations, but not the other two types of innovation.
*** p<0.01, ** p<0.05, * p<0.1

[39] Interpreting the coefficients as semi-elasticities, an increase of 1 percentage point (+0.01) in the propensity of introducing only a process innovation in a firm in service industries increases productivity by approximately 4.9 per cent, while the same increase in the propensity of introducing only a product innovation in a manufacturing firm, increases productivity by approximately 0.8 per cent. From the means of the predicted propensities in Table C5, we can see that a 0.01 percentage point change is relatively large. However, this interpretation does not take into account the standard deviations of the propensities and, in general, these results should be viewed as representing associations.

In general, the results in Table 10 do not provide any evidence for the importance of marketing innovation for productivity (with the sole exception of the case when it is combined with product innovation for manufacturing firms). While product innovation contributes to higher productivity in manufacturing and process innovation to higher productivity in service industries, organisational innovation seems to be an important supplement to these two types of innovation.

In order to relate my results to the existing literature that studies the importance of organisational innovation with respect to product and process innovation (see Section 2), I also re-estimate the productivity equation (4´) with the predicted propensities for the combinations of only product, process and organisational innovation (based on the estimation results for the first three equations in (3b´) by trivariate probit).[40] The results are presented in Table C6. These results support the importance of product innovation for higher productivity in manufacturing and of process innovation in service industries (see the results for TP100 and TP010 in Table C6). Product innovation contributes positively to higher productivity in service industries only when accompanied by organisational innovation, and a combination of all three types of innovation contributes positively to productivity in both sectors (see the results for TP101 and TP111). However, a combination of product and process innovation without organisational innovation (see the results for TP110) is associated with lower productivity (irrespective of data sample). It can be argued that, initially, this combination has a disruptive effect, but that it may lead to productivity gains in subsequent periods.[41] It can also be an indication of a negative effect of technological innovation that is not adequately supported by a change in the organisation of a firm (this finding is similar to that for service industries in Polder *et al.*, 2009). Hence, the results in Table C6 support the earlier findings on the importance of the organisational innovation for product and process innovation.

Testing for complementarity of R&D and ICT

Finally, Table C7 provides some tests of the complementarity of R&D and ICT with respect to productivity. The channels through which these two kinds of investment exert their effects are not the same. As a consequence, the question of whether R&D and ICT are complements or substitutes is a legitimate one. While the CDM model assumes that R&D influences firm productivity indirectly via an innovation output, in order to test for complementarity of R&D and ICT, I follow Hall *et al.*(2013) and include log R&D investment intensity (actual or predicted) directly in the production function together with log ICT intensity (either actual or predicted log ICT investment intensity or the actual log ICT capital intensity). Then, if the sign and significance of the estimated coefficient for an interaction term between R&D and ICT intensities is

[40] The results for the trivariate probit estimation are not reported here, but they are available from the author upon request.
[41] Testing for a lagged effect of innovation on productivity requires the introduction of dynamics in the model, which is beyond the scope of the current investigation.

positive, the two types of investment are complements in generating higher productivity; if negative, they can be seen as substitutes.

When I use the actual levels of investment (column (1) in Table C7), the interaction term is clearly zero, implying no complementarity or substitution. When I include the predicted values of both variables (column (2) in Table C7), their coefficients become large and have the opposite sign, and the coefficient for the interaction term becomes slightly negative. This result, where the ICT variable takes over much of the power of the R&D variable, is similar to the result when I tested for the endogeneity of the ICT variable in the innovation output equation (see Table C2). It can be explained by the limitations of instrumenting two somewhat similar variables using the same set of predictors. At the same time, the results for the preferred model with predicted R&D and actual ICT intensity (both the ICT investment and ICT capital intensities) indicate a weak complementarity between R&D and ICT for the Norwegian firms, i.e. the estimated coefficient for the interaction term is positive and weakly significant. All in all, these results do not provide any strong evidence for the complementarity of productivity impacts of R&D and ICT. Hence, I conclude that R&D and ICT exert their influence on productivity through unrelated channels. This result is in line with that obtained by Hall *et al*. (2013).

6. Conclusions

This paper examines the firm-level relationships between innovation, productivity and two of their major determinants, namely R&D and ICT. Two measures of innovative output are tested, i.e. different types of innovation (product, process, organisational and marketing innovation, or any innovation) and the number of patent applications. For the analysis, I use a rich firm-level data set based on the four recent waves of the *Community Innovation Survey* for Norway (CIS2004–CIS2010) and apply an extended version of the CDM model, which treats ICT as a *pervasive* input rather than as an input in the production function only.

Beyond presenting results for Norway (one of the countries with a high rate of ICT diffusion), this paper contributes to the existing literature in several ways. Firstly, in order to account for industry heterogeneity, I provide separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). Secondly, I include marketing innovation in the analysis in addition to earlier investigated product, process and organisational innovation. All four types of innovation are equally represented in the data, which makes it possible to analyse the whole set of innovation types and enables a more comprehensive understanding of the innovation process in a firm. Thirdly, I use the number of patent applications as an alternative measure for innovation. While the combination of different innovation types shows the *variety* of innovative processes in a firm, the number of patent applications reflects the *quality* of the innovation. And, finally, I control for workforce heterogeneity and check how that influences the results for ICT and R&D.

When analysing innovation output, I find that the ICT investment intensity is strongly associated with all types of innovation. This finding supports the hypothesis that ICT acts as an enabler of innovation. However, its relative importance for innovation is much lower compared to R&D intensity and workers' skills. The result for ICT intensity is robust to different model specifications and is strongest for product innovation in manufacturing and for process innovation in service industries. Not having any ICT investment is strongly negative for process and organisational innovation in manufacturing and for product and marketing innovation in service industries. Interestingly, while R&D intensity is of similar importance for innovation in both industries, skills and ICT intensity are relatively more important for innovation in manufacturing. Given much lower levels of ICT intensity in manufacturing, the latter finding suggests the conclusion that Norwegian manufacturing firms may be underinvesting in ICT compared to firms in service industries. Given that the firm innovates, the ICT investment intensity is also associated with a higher number of patent applications in manufacturing. While R&D is relatively more important for patenting in service industries, skills are relatively more important for patenting in manufacturing. Both cooperation on innovation and purchasing of R&D services from external providers are also positively related to innovating and patenting.

When analysing productivity, I find that ICT is strongly associated with productivity (independently of the model specification) and relatively more important than R&D. The results provide evidence of the importance of product innovation for productivity in manufacturing and of process innovation for productivity in service industries, with organisational innovation being an important supplement to these two types of innovation. However, the results do not provide any strong evidence of the importance of marketing innovation for productivity, since it only has a positive impact in combination with product innovation in manufacturing. Although I used a simple measure for the skill composition of the workforce, its inclusion in regressions substantially affected the predictive power of R&D and slightly affected the predictive power of ICT, indicating possible complementarities of the skill variable with R&D. As to the relationship between R&D and ICT, they seem to be neither complements nor substitutes and, hence, exert their impacts on productivity through different channels.

To sum up, I find that R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation, and ICT being more important for productivity. These results suggest that the high rate of ICT diffusion in Norway could play an important role in explaining the 'Norwegian productivity puzzle', i.e. the fact that Norway, despite having a relative low level of R&D intensity, is one of the most productive OECD countries.

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Appendix A. Data sources

R&D statistics: The R&D statistics are survey data collected by Statistics Norway every second year up to 2001, and annually after that. These data comprise detailed information about firms' R&D activities and, in particular, about total R&D expenses divided between own R&D and purchased R&D services, the number of employees engaged in R&D activities and the number of man-years worked in R&D. The 2001, 2004, 2006, 2008 and 2010 editions are combined with the Community Innovation Survey (CIS) and contain information on whether firms have introduced different types of innovation over the three-year period preceding each survey. In each wave, the sample is selected using a stratified sampling method for firms with 10–50 employees, whereas all firms with more than 50 employees are included. The strata are based on industry and firm size. Each survey contains about 5 000 firms (6 000 in the most recent surveys), although not all of them provide complete information.

Norwegian patent database: This database contains data on the total number of Norwegian patents applied for by the firm in the given year (available from 1990). These data are obtained by Statistics Norway from the Norwegian Patent Office and contain a firm identifier that allows them to be merged with other data sources.

The Investment statistics: The term 'Investment statistics' is a general name for the different industrial activities statistics (e.g. Manufacturing statistics, Building and Construction statistics, etc.), which are based on General Trading Statements, provided in an appendix to the tax return. They all have the same structure and include information about production, input factors and investments at the firm level. Since 2002, these data have comprised information about annual investments in hardware (purchased) and software (both purchased and on own account). The Investment statistics are organised according to the Standard Industrial Classification SN2002 (SN2007 since 2007)[42] and are collected for the following industries (NACE-codes from SN2002 in brackets):

- Manufacturing (NACE 15-37)
- Building and construction (NACE 45)
- Wholesale trade (NACE 51)
- Transport, storage and communication (NACE 60-64)
- Business related services (NACE 72-74)
- Other industries (NACE 5, 10-14, 40-41, 55, 59, 65-67, 90, 93).

Accounts statistics: In the accounts statistics, a firm is defined as 'the smallest legal unit comprising all economic activities engaged in by one and the same owner'. It corresponds in general to the concept of a company. A firm can consist of one or more establishments that are the geographically local units conducting

[42] Since I have codes from both SN2002 and SN2007 for CIS2008 data, I use NACE codes from SN2002 in my analysis in order to avoid as far as possible the misspecification of a firm's industry (that is possible when one starts using a new classification).

economic activity within an industry class. Another unit is the consolidated group, which consists of a parent company and one or more subsidiaries. Both the parent company and the subsidiaries are firms as defined here. All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, and, in particular, information about operating revenues, operating costs and operating profit/loss, labour costs, and the book values of the firm's tangible fixed assets at the end of a year, their depreciation and write-downs.

The Register of Employers and Employees (REE) contains information about each individual employee's contract start and end, wages and contract working hours. Since both the firm identification number and the personal identification number are included, these data can easily be aggregated to the firm level.

The National Education Database (NED) includes individually based statistics on education and contains a six-digit number, where the leading digit describes the educational level of the person. I use this data set to obtain information on the length of education of employees. This information was first integrated into a common data base with REE and then aggregated to the firm level.

Table A1 – Distribution across industries of the final sample (14 533 observations)

Industry	NACE (SN2002)	No. obs.	Share of obs.
Mining and extraction	10-14	167	1.1 %
Manufacturing:	15-36	6199	42.7 %
Food products and beverages	15	834	5.7 %
Textiles	17	198	1.4 %
Other textile products	18-19	97	0.7 %
Wood and wood products	20	445	3.1 %
Pulp, paper and paper products	21	123	0.9 %
Publishing and printing	22	655	4.5 %
Chemicals and chemical products	24	244	1.7 %
Rubber and plastic products	25	210	1.4 %
Other non-metallic mineral products	26	283	2.0 %
Basic metals	27	174	1.2 %
Fabricated metal products (excl. machinery)	28	669	4.6 %
Machinery and equipment	29	674	4.6 %
Electrical machinery	31	269	1.9 %
Computers, radio/TV and communication equip.	30,32	132	0.9 %
Medical, precision and optical instruments	33	247	1.7 %
Motor vehicles and trailers	34	158	1.1 %
Other transport equipment	35	443	3.1 %
Furniture	36	344	2.4 %
Construction	45	1791	12.3 %
Service industries:	51-74	6143	42.3 %
Wholesale trade	51	1854	12.8 %
Land transport	60	505	3.5 %
Water and air transport	61-62	319	2.2 %
Supporting and auxiliary transport activities	63	483	3.3 %
Post and telecommunications	64	250	1.7 %
Computers and related activities	72	1288	8.9 %
Research and development	73	116	0.8 %
Other business-related services	74	1342	9.2 %
Other industries	37,40,41,90-92	219	1.5 %
Total		14533	100 %

Table A2 – Descriptive statistics on key variables for the final sample (14533 observations)

Variable	Mean	Std. Dev.	Min	Median	Max
Value added (VA) per employee	610.021	380.685	65.940	525.999	4878.422
Number of employees	92.639	318.714	5	30	18815
Firm age	17.479	15.556	.5	14	116
ICT capital services per VA	.034	.094	0	.015	3.505
Tangible capital services per VA	.060	.107	0	.025	3.257
Share of high-skilled	.289	.267	0	.185	1
Part of a group (dummy)	.617	.486	0	1	1
Market location: local/regional (dummy)	.516	.499	0	1	1
Market location: national (dummy)	.331	.470	0	0	1
Market location: European (dummy)	.091	.287	0	0	1
Market location: world (dummy)	.062	.241	0	0	1
Cooperation in innovation (dummy)	.169	.375	0	0	1
Purchased R&D (dummy)	.133	.339	0	0	1
R&D investors, R>0 (dummy)	.301	.459	0	0	1
ICT investors, ICT>0 (dummy)	.893	.309	0	1	1
R&D intensity for R&D investors	32.519	101.183	0	0	1800.871
ICT intensity for ICT investors	21.093	77.369	0	7.437	3027.445
Any type of innovation (dummy)	.479	.499	0	0	1
Applied for a patent (dummy)	.101	.301	0	0	1
Number of patent applications	.209	1.601	0	0	76

Table A3 – Correlations between key variables, firms with positive R&D (4377 observations)

	Log *Y/L*	Log *R/L*	Log *ICT/L*	*inno*	*sum-pat*	Log *L*	*h*	Market location	Part of a group	Receive subsidy	Coop.	Purch. R&D
logVAemp	1											
Log R&D intensity	0.09	1										
Log ICT intensity	0.28	0.31	1									
Dummy for innovation	-0.02	0.15	0.04	1								
No. of patent appl.	0.16	0.09	0.02	0.05	1							
Log employment	0.18	-0.44	-0.12	0.02	0.19	1						
Share of high skilled	0.22	0.49	0.45	0.02	0.06	-0.28	1					
Market location	0.09	0.21	0.04	0.07	0.15	0.08	0.09	1				
Part of a group	0.17	-0.15	-0.02	-0.02	0.05	0.39	-0.12	0.10	1			
Receive subsidy	-0.08	0.33	0.03	0.11	0.08	-0.08	0.10	0.09	-0.07	1		
Cooperation	0.05	0.09	-0.00	0.09	0.09	0.11	0.03	0.11	0.07	0.15	1	
Purchased R&D	0.05	0.03	-0.08	0.07	0.09	0.21	-0.12	0.14	0.12	0.09	0.30	1

Appendix B. Definitions and examples of different types of innovation

The Oslo Manual defines an 'innovation' as: "...the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organisation or external relations." (OECD, 2005, p. 46)

A *product innovation* is the introduction of a good or service that is significantly improved with respect to its characteristics or intended uses and includes significant improvements in technical specifications, components and materials, incorporated software and user friendliness or other functional characteristics (OECD, 2005, p. 48). Design changes which do not involve a significant change in the product's functional characteristics or intended use, such as a new flavour or colour option, are not product innovations. Product innovations in services can include significant improvements in how the product is provided, such as home pick-up or delivery services, or other features which improve efficiency or speed.

A *process innovation* is a new or significantly improved production or delivery method, including significant changes in techniques, equipment and/or software (OECD, 2005, p. 49). For example, introduction of a new automation method on a production line, or in the context of ICT, developing electronic system linkages to streamline production and delivery processes, are both process innovations.

With respect to services, it is often difficult to distinguish a product and process innovation. The Oslo Manual (OECD, 2005, p. 53) contains the following guidelines to distinguish these two types of innovation: if the innovation involves new or significantly improved characteristics of the service offered to customers, it is a product innovation; if the innovation involves new or significantly improved methods, equipment and/ or skills used to perform the service, it is a process innovation.

An *organisational or managerial innovation* is the implementation of a new or significantly improved method of the firm's business practices, workplace organisation or external relations. It requires more than mere organisational change or restructure. In fact, the organisational method must not have been previously used by the business and must be the results of strategic decisions taken by management (OECD, 2005, p. 49). Examples include implementation a new method for distributing responsibilities and decision making among employees, decentralising group activity, developing formal or informal work teams, new types of external collaboration with research organisations or the use of outsourcing or sub-contracting for the first time (OECD, 2005, p. 52).

A *marketing innovation* is the implementation of a new or significantly improved marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing. The marketing method must not have been previously used by the firm and must be part of a new marketing concept or strategy representing a significant departure from the firm's existing methods (OECD, 2005, p. 50).

Appendix C. Different issues on the model estimation

Table C1 – Sample selection model for R&D and ICT choice (all firms)

Dependent variables	R>0	(1)^ Log R&D per emp	(2)~ Log R&D per emp	ICT>0	(3)^ Log ICT per emp	(4)~ Log ICT per emp
Log employment	0.104	-0.765***	-0.666***	0.518***	0.091*	0.091*
	[0.063]	[0.096]	[0.094]	[0.063]	[0.051]	[0.051]
Log employment squared	0.003	0.036***	0.030***	-0.043***	-0.010	-0.010
	[0.007]	[0.011]	[0.011]	[0.008]	[0.006]	[0.006]
Market location: National	0.331***	0.245***	0.312***	0.081**	0.153***	0.153***
	[0.035]	[0.052]	[0.051]	[0.036]	[0.026]	[0.026]
Market location: European	0.521***	0.461***	0.558***	0.041	0.198***	0.198***
	[0.053]	[0.068]	[0.066]	[0.061]	[0.045]	[0.045]
Market location: World	0.601***	0.702***	0.802***	-0.022	0.312***	0.312***
	[0.062]	[0.075]	[0.072]	[0.073]	[0.052]	[0.052]
Part of a group	-0.046	0.103**	0.101**	-0.077**	0.079***	0.079***
	[0.035]	[0.046]	[0.046]	[0.034]	[0.026]	[0.026]
Hampering factor: high costs	0.280***	-0.053**	-0.011	0.041**	-0.012	-0.012
	[0.018]	[0.023]	[0.022]	[0.020]	[0.013]	[0.013]
Hampering factor: staff	0.136***	0.084***	0.104***	0.028	0.046***	0.046***
	[0.021]	[0.022]	[0.022]	[0.025]	[0.016]	[0.016]
Hampering factor: information	0.111***	-0.023	-0.010	0.035	-0.018	-0.018
	[0.024]	[0.026]	[0.026]	[0.029]	[0.019]	[0.019]
Cooperation in innovation		0.241***	0.252***		0.188***	0.188***
		[0.039]	[0.039]		[0.031]	[0.031]
Received subsidies		0.719***	0.738***		0.137***	0.137***
		[0.041]	[0.041]		[0.032]	[0.032]
Positive investment history¤	1.732***			0.914***		
	[0.042]			[0.076]		
Chi-square or F-test for age dummies		58.80***	0.51	20.23**		1.90*
Chi-square or F-test for industry dummies		828.21***	20.30***	2419.54***		80.18***
Chi-square or F-test for regional dummies		23.54**	2.43**	53.49***		8.13***
Chi-square or F-test for time dummies		165.66***	2.29*	765.45***		237.19***
Correlation coefficient rho		-0.239***		-0,003		
Chi-square for selection		27.17***		0.01		
R-squared		0.50	0.49	0.29		0.29
Number of obs.(uncensored)		14533(4377)	4377	14533(12982)		12982

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE 51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
^ Estimated by full maximum loglikelihood as a Heckman selection model; ~ estimated by OLS.
¤ A dummy for the positive R&D investment in any of the 3 previous years in model (1) and a dummy for positive ICT capital lagged two years in model (3).
*** p<0.01, ** p<0.05, * p<0.1

Table C2 – Robustness checks for inclusion of the skill variable in the innovation output equation (by industry)

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Log R&D intensity	0.878***	0.836***	0.773***	0.860***	0.803***	0.762***	0.850***	0.812***	0.685***
(predicted)	[0.042]	[0.043]	[0.049]	[0.061]	[0.063]	[0.070]	[0.062]	[0.062]	[0.077]
Interaction of predicted			0.169**			0.177			0.239***
R&D and skilled share			[0.068]			[0.146]			[0.089]
Share of high skilled		0.500***	-0.150		0.780***	0.125		0.385***	-0.559
		[0.076]	[0.274]		[0.143]	[0.571]		[0.096]	[0.365]
Log ICT intensity	0.055***	0.046***	0.048***	0.093***	0.074***	0.076***	0.031**	0.026*	0.029*
	[0.010]	[0.010]	[0.010]	[0.017]	[0.018]	[0.018]	[0.014]	[0.015]	[0.015]
Zero ICT	-0.113**	-0.125***	-0.116***	-0.127*	-0.165**	-0.159**	-0.120	-0.118	-0.108
	[0.044]	[0.044]	[0.045]	[0.066]	[0.066]	[0.066]	[0.073]	[0.073]	[0.073]
Log employment	0.781***	0.749***	0.742***	0.855***	0.812***	0.803***	0.711***	0.678***	0.673***
	[0.059]	[0.059]	[0.059]	[0.095]	[0.096]	[0.096]	[0.085]	[0.086]	[0.085]
Log employment squared	-0.032***	-0.030***	-0.030***	-0.041***	-0.040***	-0.039***	-0.029***	-0.026***	-0.028***
	[0.007]	[0.007]	[0.007]	[0.012]	[0.012]	[0.012]	[0.010]	[0.010]	[0.010]
Cooperation: National	0.567***	0.564***	0.566***	0.558***	0.567***	0.570***	0.536***	0.523***	0.519***
	[0.050]	[0.050]	[0.050]	[0.071]	[0.071]	[0.071]	[0.076]	[0.077]	[0.077]
Cooperation: Scandinavia	0.326***	0.335***	0.338***	0.440***	0.448***	0.449***	0.282*	0.294*	0.315*
	[0.101]	[0.100]	[0.100]	[0.138]	[0.140]	[0.140]	[0.164]	[0.162]	[0.162]
Cooperation: EU	0.031	0.026	0.020	0.144	0.142	0.140	-0.038	-0.044	-0.056
	[0.097]	[0.097]	[0.097]	[0.149]	[0.150]	[0.151]	[0.145]	[0.143]	[0.144]
Cooperation: World	0.214*	0.198	0.196	0.272	0.249	0.247	0.300*	0.289*	0.285*
	[0.121]	[0.121]	[0.121]	[0.223]	[0.221]	[0.222]	[0.167]	[0.166]	[0.167]
Purchased R&D	0.627***	0.622***	0.626***	0.669***	0.663***	0.662***	0.597***	0.590***	0.601***
	[0.052]	[0.052]	[0.052]	[0.068]	[0.068]	[0.068]	[0.088]	[0.088]	[0.088]
Pseudo *R*-squared	0.2217	0.2243	0.2247	0.2376	0.2416	0.2418	0.1853	0.1875	0.1886
Log likelihood	-7830.13	-7804.49	-7800.69	-3251.76	-3234.75	-3233.96	-3468.72	-3459.13	-3454.74
Number of obs. (non-zero)	14533(6967)			6199(3412)			6145(2997)		

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and for the whole sample, mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Probit model estimates for having at least one innovation.
*** p<0.01, ** p<0.05, * p<0.1.

Table C3 – Exploring endogeneity of ICT variable in the innovation output equation (all firms)

Innovation output:	Any type of innovation^			Number of patent applications~		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT variable:	Observed ICT intensity	Lagged ICT intensity	Predicted ICT intensity	Observed ICT intensity	Lagged ICT intensity	Predicted ICT intensity
Log R&D intensity (predicted)	0.836***	0.842***	0.430***	0.898***	0.886***	0.421**
	[0.043]	[0.043]	[0.093]	[0.093]	[0.093]	[0.201]
Share of high skilled	0.500***	0.487***	0.535***	1.656***	1.618***	1.731***
	[0.076]	[0.077]	[0.075]	[0.219]	[0.220]	[0.219]
Log ICT intensity	0.046***	0.056***	1.173***	0.086***	0.058	1.658***
	[0.010]	[0.012]	[0.235]	[0.030]	[0.043]	[0.563]
Zero ICT	-0.125***	-0.114		0.408***	-0.639	
	[0.044]	[0.167]		[0.158]	[0.489]	
Log employment	0.749***	0.769***	0.340***	1.145***	1.144***	0.597**
	[0.059]	[0.060]	[0.104]	[0.153]	[0.165]	[0.264]
Log employment squared	-0.030***	-0.031***	-0.005	-0.031**	-0.033*	0.005
	[0.007]	[0.007]	[0.009]	[0.016]	[0.017]	[0.022]
Cooperation: National	0.564***	0.565***	0.477***	0.039	0.036	-0.102
	[0.050]	[0.051]	[0.053]	[0.088]	[0.090]	[0.094]
Cooperation: Scandinavia	0.335***	0.337***	0.321***	0.041	0.087	0.031
	[0.100]	[0.102]	[0.099]	[0.101]	[0.103]	[0.101]
Cooperation: EU	0.026	0.033	0.023	0.241**	0.275***	0.220**
	[0.097]	[0.098]	[0.095]	[0.104]	[0.105]	[0.105]
Cooperation: World	0.198	0.180	0.187	0.176	0.220*	0.168
	[0.121]	[0.121]	[0.119]	[0.113]	[0.116]	[0.114]
Purchased R&D	0.622***	0.623***	0.643***	0.369***	0.360***	0.381***
	[0.052]	[0.053]	[0.052]	[0.080]	[0.083]	[0.082]
Log likelihood	-7830.1328	-7609.6193	-7816.435	-4724.49	-4604.62	-4726.01
Number of observations	14533	14164	14533	14533	14164	14533
Non-zero observations	6967	6808	6967	1467	1432	1467

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
^ Estimated by maximum loglikelihood as simple probit model; ~ Estimated by pseudo maximum loglikelihood as a zero inflated negative binomial count data model.
*** p<0.01, ** p<0.05, * p<0.1.

Table C4 – Estimation results – Innovation output: Four types of innovation (all firms)

Innovation type:	New product		New process		Organisational		Marketing	
	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
All firms (14533 observations, 8554 firms)								
Predicted R&D intensity (log)	0.895 ***	0.043	0.541 ***	0.041	0.246 ***	0.039	0.387 ***	0.038
Share of high-skilled	0.694 ***	0.084	0.036	0.082	0.245 ***	0.082	0.277 ***	0.076
ICT intensity (log)	0.054 ***	0.012	0.042 ***	0.012	0.044 ***	0.011	0.022 **	0.011
Zero ICT investment	-0.107 **	0.054	-0.123 **	0.053	-0.057	0.053	-0.110 **	0.048
Employment (log)	0.565 ***	0.063	0.317 ***	0.062	1.141 ***	0.059	0.345 ***	0.055
Employment squared (log)	-0.014 *	0.007	0.000	0.007	-0.086 ***	0.007	-0.016 ***	0.006
Cooperation: National	0.509 ***	0.046	0.485 ***	0.043	0.359 ***	0.042	0.438 ***	0.041
Cooperation: Scandinavia	0.178 **	0.073	0.300 ***	0.064	0.225 ***	0.060	0.230 ***	0.061
Cooperation: EU	0.130 *	0.074	-0.081	0.065	0.064	0.063	0.041	0.064
Cooperation: World	-0.089	0.085	-0.016	0.076	0.025	0.069	-0.001	0.070
Purchased R&D	0.520 ***	0.044	0.362 ***	0.042	0.214 ***	0.040	0.208 ***	0.041
Number of non-zero obs.	4189		3118		3145		3748	
rho21	0.523 ***	0.015						
rho31	0.273 ***	0.017						
rho41	0.532 ***	0.014						
rho32	0.426 ***	0.016						
rho42	0.375 ***	0.015						
rho43	0.459 ***	0.015						
Chi-square for all rho=0^	3504.4 ***							
Log likelihood	-24017.1							

Notes: All regressions include a constant, firm age, industry, location and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level.

Dependent variables: binary indicators for different types of innovation. Estimated as a quadrivariate probit model using the program *mvprobit* in Stata (see Cappellari and Jenkins, 2003) with the number of draws for the GHK simulator equal to 120.

^ This is the test that all correlations $\rho_{jk} = \rho_{kj}$ between η^k and η^j in (3b´), $j, k = 1,2,3,4$ and $j \neq k$, are jointly equal to zero.

*** p<0.01, ** p<0.05, * p<0.1

Table C5 – Predicted propensities from the quadrivariate probit (QP) knowledge production function (by industry)

	All firms		Manufacturing		Services	
Combinations*	Observed frequencies	Predicted Mean	Observed frequencies	Predicted Mean	Observed frequencies	Predicted Mean
QP1111	0.0527	0.0593	0.0644	0.0725	0.0548	0.0599
QP1110	0.0202	0.0217	0.0268	0.0273	0.0171	0.0204
QP1101	0.0411	0.0384	0.0513	0.0463	0.0433	0.0442
QP1011	0.0246	0.0242	0.0318	0.0304	0.0241	0.0251
QP0111	0.0103	0.0107	0.0113	0.0110	0.0112	0.0116
QP0011	0.0266	0.0224	0.0231	0.0197	0.0303	0.0254
QP0101	0.0089	0.0088	0.0102	0.0113	0.0098	0.0094
QP0110	0.0189	0.0149	0.0197	0.0163	0.0176	0.0133
QP1001	0.0441	0.0418	0.0552	0.0540	0.0470	0.0430
QP1010	0.0150	0.0120	0.0186	0.0167	0.0158	0.0118
QP1100	0.0338	0.0309	0.0365	0.0356	0.0386	0.0332
QP0001	0.0495	0.0616	0.0510	0.0625	0.0524	0.0660
QP0010	0.0482	0.0607	0.0411	0.0530	0.0456	0.0600
QP0100	0.0287	0.0383	0.0365	0.0454	0.0236	0.0355
QP1000	0.0568	0.0692	0.0732	0.0844	0.0566	0.0739
QP0000	0.5206	0.5156	0.4496	0.4451	0.5123	0.5034
Number of obs.		14333		6199		6145
Number of draws		120		80		80

*QP refers to the combinations of the Quadrivariate Probit model for four innovation types: product, process, organisational and marketing innovation, e.g. QP1001 refers to the combination [1,0,0,1], i.e. the firm has introduced both product and marketing innovations, but not the other two types of innovation.

Table C6 – Estimation results – Productivity: with combinations of product, process and organisational innovation

Sample:	All firms		Manufacturing		Services	
TP111 (predicted)	0.454***	[0.106]	0.313**	[0.130]	0.245*	[0.137]
TP110 (predicted)	-1.075***	[0.164]	-0.559***	[0.189]	-0.671***	[0.209]
TP101 (predicted)	0.011	[0.305]	-0.269	[0.326]	0.835**	[0.363]
TP011 (predicted)	0.049	[0.438]	-0.274	[0.455]	0.300	[0.589]
TP001 (predicted)	0.164	[0.234]	-0.021	[0.319]	0.340	[0.283]
TP010 (predicted)	-0.238	[0.422]	-0.291	[0.394]	2.061***	[0.518]
TP100 (predicted)	1.186***	[0.194]	0.826***	[0.206]	0.277	[0.232]
ICT capital intensity	0.091***	[0.005]	0.101***	[0.006]	0.092***	[0.007]
Tangible capital intensity	0.084***	[0.004]	0.086***	[0.005]	0.080***	[0.005]
Share of high skilled	0.357***	[0.040]	0.376***	[0.062]	0.521***	[0.041]
Log employment	0.069**	[0.033]	0.081**	[0.038]	0.054	[0.048]
Log employment squared	-0.005	[0.003]	-0.002	[0.004]	-0.007	[0.005]
R-squared	0.30		0.36		0.24	
Number of observations	14427		6162		6086	

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Manufacture of food products and beverages (NACE15) for manufacturing firms or Wholesale (NACE51) for firms in services and, for the whole sample, mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
TP refers to the combinations of the Trivariate Probit model for three innovation types: product, process and organisational innovation, e.g. TP101 refers to the combination [1,0,1], i.e. the firm has introduced both product and organisational innovations, but not process innovation.
*** p<0.01, ** p<0.05, * p<0.1

Table C7 – Performing formal R&D and ICT: complementarity tests for productivity (all firms)

R&D and ICT variables:	(1) Both actual	(2) Both predicted	(3) R&D predicted, ICT actual	(4) R&D predicted, ICT capital actual
Log R&D intensity	0.017**	-0.100***	0.050***	0.036**
	[0.007]	[0.034]	[0.015]	[0.016]
Log ICT intensity	0.078***	0.702***	0.047***	0.082***
	[0.004]	[0.077]	[0.012]	[0.015]
R&D*ICT	-0.001	-0.018**	0.009**	0.009*
	[0.002]	[0.008]	[0.004]	[0.004]
Log tangible capital	0.089***	0.098***	0.089***	0.076***
per employee	[0.004]	[0.004]	[0.004]	[0.004]
Log employment	0.125***	-0.045	0.171***	0.148***
	[0.020]	[0.034]	[0.020]	[0.020]
Log employment squared	-0.009***	0.002	-0.011***	-0.009***
	[0.002]	[0.003]	[0.002]	[0.002]
Observations	14533	14533	14533	14427
R-squared	0.25	0.23	0.26	0.27

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
*** p<0.01, ** p<0.05, * p<0.1